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Uncertainty analysis in ship performance monitoring

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ABSTRACT

There are increasing economic and environmental incentives for ship owners and operators to develop tools to optimise operational decisions, particularly with the aim of reducing fuel consumption and/or maximising profit. Examples include real time operational optimisation, maintenance triggers and evaluating technological interventions. Performance monitoring is also relevant to charter party analysis, vessel benchmarking and to better inform policy decisions. The ship on-board systems and systems in which they operate are complex and it is common for data modelling and analysis techniques to be employed to extract trends. All datasets and modelling procedures have an inherent uncertainty and to aid the decision maker, the uncertainty can be quantified in order to fully understand the economic risk of a decision; an unacceptable risk requires further investment in data quality and data analysis techniques. This paper details and categorises the relevant sources of uncertainty in performance measurement, and presents a method to quantify the overall uncertainty in a ship performance indicator based on the framework of the "Guide to Uncertainty in Measurement using Monte Carlo Methods". A sensitivity analysis conducted on the sources of uncertainty highlights the relative importance of each. The two major data acquisition strategies, continuous monitoring and noon reported, are compared.

1. Introduction

Ship operational performance is a complex subject, not least because of the various systems and their interactions in which a ship operates; the major factors are presented in Fig. 1. At the ship level the ship design, machinery configurations and their efficiencies determine the onboard mechanical, thermal and electrical energy flows which, despite automation built in to the configuration mode settings at the ship design phase, there is still an appreciable level of human interaction during day-to-day operations. The environmental conditions (sea state, wind speed, sea/air temperature etc.) are dynamic, largely unpredictable and complicated to quantify, due in part to the characteristics of the chaotic and turbulent flow fields by which they are determined. These environmental conditions exert an influence on the ship's resistance and therefore the ship power requirements in differing relative quantities. The rate of deterioration in ship performance (engine, hull and propeller) is dependent on a large array of variables; including the quality and type of hull coating and the frequency of hull and propeller cleaning which are also dependent on the ocean currents, temperature and salinity in which the ship operates. Further, the shipping industry operates in an economic sphere in which the global consumption of goods and global energy demand, and conditions in the various shipping markets determine operating profiles, costs and prices (see for example Lindstad et al. (2013) which also explores environmental effects). In addition, technological investment, fuel efficiency and savings are complicated by the interactions between ship owner–charterer–manager (Agnolucci et al., 2014).

Data collection, either through daily noon reporting procedures or high frequency, automatic data acquisition systems, and data processing techniques such as filtering and/or modelling have so far proven to be useful tools in capturing and quantifying some of the intricacies and nuances of these interactions to better understand the consequences of operational decisions. These datasets and modelling outputs are applied in areas such as real time operational optimisation including trim adjustments, maintenance triggers, predicting and evaluating the performance of new technologies or interventions, particularly for cost benefit analysis, fault analysis, charter party analysis, vessel benchmarking and to better inform policy decision making.

The need to conduct uncertainty analysis is linked to the amplitude of the noise or scatter in the data relative to the underlying, trends that are to be extracted. The ship system

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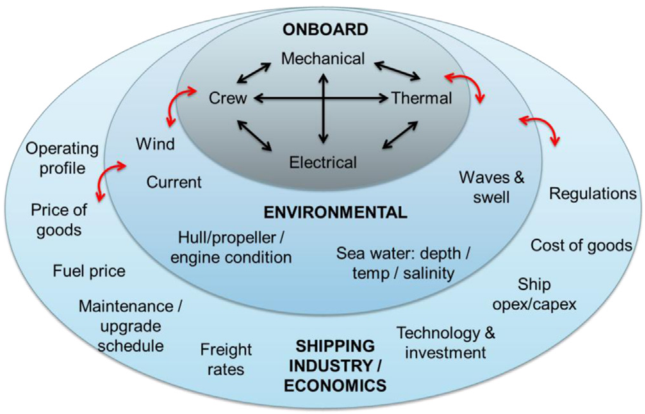

Fig. 1. Ship performance influential factors.

interactions give rise to scatter in the data, not only from inherent sensor precision but also from estimated, unobservable and/or unmeasurable variables. According to the central limit theorem (assuming independent, identical distributions), over time the scatter will tend to a normal distribution with zero mean. This time period is dependent on the data acquisition and processing strategy; the temporal resolution of sensors and data collection frequency, the sensor precisions and human interactions in the collection process and the modelling or filtering methods all play a part. There are also uncertainties in the data that will introduce a potentially significant bias in the results and this too needs to be understood and evaluated. The magnitude of the underlying trends to be identified are also a function of the modelling application; for evaluating the performance of new technologies the signal delta, i.e. the improvement in ship performance, may be a step change of the order of 1–3% (as in the case of propeller boss cap fins) or up to 10–15% as in the case of hull cleaning or new coating applications where analysis of trends in the time domain is also necessary. Therefore, the ideal measurement uncertainty depends on the application and this drives the required data acquisition strategy which is of course constrained by costs; economic, time and resources.

Data acquisition strategies are broadly separated into two dominant dataset types. Noon report (NR) datasets are coarse but convenient and cheap to compile. They are currently in widespread use across the global fleet. The frequency of recording is once every 24 h (time zone changes allowing) and the fields reported are limited, generally included as a minimum are ship speed and position, fuel consumption, shaft rotational speed, wind speed derived Beaufort number, date/time and draught. Given the economic and regulatory climate there has been a shift towards more complete, automatic measurement systems referred to in this paper as continuous monitoring (CM) systems. The uptake of these has been limited by retrofit installation costs in service, while improved data accuracy, speed of acquisition, high sampling frequency (5 min) and repeatability are cited as the key drivers for adoption. All datasets and modelling procedures have an inherent uncertainty associated with them and as a prerequisite the uncertainty must be quantified in order to fully understand the economic risk of a technological/operational decision to be made. The risk of the decision is defined by the accuracy of the performance measurement and this is determined by the uncertainty of the data relative to the magnitude of the change in ship performance, the former depends on the data acquisition strategy (NR vs. CM, for example) and has an associated cost, while the latter depends on the application (the technological/operational decision being made) and has an associated cost and benefit, both economic and environmental. If the economic risk is deemed unacceptable then it makes sense to re-evaluate investment in data quality and data analysis techniques.

The uncertainty is also important because of the risks and costs that are associated with the decision derived from the measured ship's performance. The desire to quantify these (in other industries) has led to the field of research into methods for risk-based decision making. The application of these methods to the shipping industry is also important, for example, measurement and verification is cited as a key barrier to the market's uptake of fuel efficient technologies and their retrofit. In order to secure capital, investment projects must be expected to yield a return in excess of the ROI of other projects competing for capital or perhaps in excess of some pre-defined minimum (Stulgis et al., 2014). The ability to weigh the economic risk of capital investment against the certainty of the effectiveness of a fuel efficient technology is therefore key. A study of the sensitivities of the uncertainty in the ship performance measurement is pertinent to inform where resources can be invested most effectively in order to reduce the overall uncertainty to the desired level; is the cost of obtaining additional information outweighed by the value of the improvement in the model from which the performance estimate is derived? (Loucks et al., 2005). It is of course not just financial but legislative drivers that are significant in the uptake of fuel efficient technologies and modelling ship performance in this case is also important in order to establish if new policies have been effective either from a fleet wide or total global emissions perspective.

An overview of uncertainty analysis methods and their application to ship performance measurement uncertainty is described in Section 2. This paper is based on a similar framework but also employs an underlying time domain algorithm to simulate the ship's operational profile and performance trends in order to propagate the errors through the model by Monte Carlo simulation. Section 3 presents a brief overview of ship performance methods and introduces the ship performance indicator used in this study; the sources of uncertainty in this measurement are then detailed and quantified in Section 5. This method is validated using continuous monitoring data from 1 ship; the validation results are presented in Section 5.4. A sensitivity analysis is employed in Section 7 to examine the effect of sensor characteristics and data acquisition sampling frequencies on the performance indicator uncertainty given the length of the performance evaluation period. Different acquisition strategies (based broadly on noon reporting and continuous monitoring acquisition strategies) are then compared. The type of data processing has also been considered and while this paper focuses on a basic ship model using filtered data, there is ongoing work that explores how the uncertainty may be reduced by using a ship performance model (normalising approach). Sections 8 and 9 present the results, discussion and conclusions.

2. Uncertainty analysis methodology

The aim of an uncertainty analysis is to describe the range of potential outputs of the system at some probability level, or to estimate the probability that the output will exceed a specific threshold or performance measure target value (Loucks et al., 2005). The main aim in the uncertainty analysis deployed in the quantification of performance trends is to estimate the parameters of the output distribution and to conduct a sensitivity analysis to estimate the relative impact of input uncertainties.

Uncertainty analysis methods have evolved in various ways depending on the specific nuances of the field in which they are applied. However, a key document in the area of uncertainty evaluation is the 'Guide to the expression of uncertainty in