Noon report Data Uncertainty

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Abstract

Noon report data is a low resolution dataset (sampling frequency of approximately 24 hours) from which it is possible to extract the principal variables required to define the ship's performance in terms of fuel consumption. There are increasing economic and environmental incentives for ship owners and operators to develop tools to optimise operational decisions with the aim of reducing fuel consumption and/or maximising profit. Further, a ships current performance needs to be measured in order for fuel savings from technological interventions to be assessed. These tools and measurements may be based on models developed from historical trends that are extracted from noon reports; however there is inherent uncertainty in this dataset. As a prerequisite the uncertainty must be quantified to understand fully the potential and limitations of predictive models from which operational tools may be designed and of statistical models from which technological interventions are assessed. This paper initially presents a method for quantifying the uncertainty in reported fuel consumption using between two months and one year's worth of data from 89 ships. The subsequently calculated confidence is then compared to the uncertainty in the data acquired from an on board continuous monitoring system.

Keywords: noon report; uncertainty; regression; onboard monitoring

1. Introduction

There is a vast set of variables that describe a ship's performance for a specific operating condition and at a given point in time. In this paper, the dependent variable of ship performance refers to the ship's fuel consumption at the operating condition. The independent variables are limited by the fields included in the noon report (NR) dataset, these are shaft rotational speed (RPM), wind speed derived Beaufort number (BF), time (t) and the loading condition (L) which is a binary input; loaded or ballast. The origin of the noon report data analysed in this paper is a fleet of tankers of various size and type.

Given the economic and regulatory climate there has been a shift towards more complete, automatic measurement systems referred to here as continuous monitoring (CM) systems. The uptake of these is generally limited by installation costs while improved data accuracy, speed of acquisition, high sampling frequency (5minutes) and repeatability are cited as the key drivers. Generally, the majority of ships do not have CM systems installed whilst noon reports are in widespread use across the global fleet therefore a study and comparison of the uncertainty in both is relevant. There is one LNG carrier for which data is available from noon reports and CM systems, in this case actual wind speed and direction is reported therefore allowing true wind speed to be used instead of BF number. The noon reported binary loading variable is a proxy for the effect of the change in draft due to the ship's loading condition, in the CM dataset this is calculated as an average from the numeric forward and aft draft inputs. The remainder of this introduction gives some background information on the various sources of the uncertainties.

Each sensor has an associated accuracy in its measurements; fuel flow meter accuracy for example ranges between 0.05 per cent and 3 per cent depending on the type, the manufacturer, the flow characteristics and the installation [J. Faber, D. Nelissen et al. (2013)]. As with all sensors, errors also increase if they are poorly maintained or calibrated. Inaccurate sensors will lead to measurement bias and the measure is limited by the sensor repeatability and resolution, there are potential issues of stuck

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sensors. The measurement of wind speed for the Beaufort scale measure is instantaneous and therefore does not capture the variability in the weather over the entire 24 hours, it additionally involves instrument error, and possible error associated with the height of the sensor above the deck.

Human error may occur in any measurements when operating, reading or recording sensor values if the report completion is not automated. For example the noon data entry may not occur at exactly the same time each day, the recording of 'time spent steaming' may not be adjusted to compensate for crossing time zones and it is possible that different sensors are used to populate the same field, for example, some crew may report speed from the propeller RPM and others report speed over ground.

Aleatory uncertainty is the inherent variability in any of the measured variables; it is omnipresent and unpredictable. Typically environmental effects, i.e. the Beaufort number, are associated with a large degree of aleatory error which is exacerbated by the low resolution of the Beaufort scale itself and therefore rounding errors when converting from wind speed. Random fluctuations of fuel grade (although these are limited by the fuel standard grading system) and of fuel density and engine degradation all contribute to fuel consumption measurement uncertainty if calculated from flow meters using assumed values. The limitation of the binary 'loading' field leads to random rounding errors if the ship is actually partially loaded.

The low resolution of the noon reports may lead to incorrect 24hour average values being recorded, particularly for Beaufort scale and ship speed where effect on fuel consumption of accelerations/decelerations and ship maneuverings cannot be captured or even reported to have occurred. The mean or mode or the instantaneous rather than average may be may recorded depending on the crew.

2. Aim and Objective of the study

- To develop analysis procedures for estimating the relationship between the key independent variables that influence fuel consumption, thereby minimising epistemic uncertainty
- To estimate/quantify the influence of aleatory and measurement uncertainty on overall fuel performance quantifications
- To estimate quality of the predictions that can be made using a model based on the input data

3. Method

If perfect information is available, uncertainty can be quantified by comparing a benchmark with a given measurement. In the case of the ships for which noon report data is available, there is no authoritative benchmark. Consequently, this has to be derived from available data, which has its own inherent uncertainties.

The approach taken is to use a regression model, in combination with knowledge about the physics influencing fuel consumption, to capture the physical interactions between parameters. Through statistical control of measured variables the model should describe as much of the variation in the data as possible and therefore enable conclusions about influences and sensitivities of ship performance to the different input parameters to be drawn.

If fuel consumption or its dependent variables had no measurement or aleatory uncertainty, then the R^2 would be 1 and the standard error of the estimates would be zero. This is not practically possible firstly because of the previously discussed aleatory/measurement uncertainty in the dataset and secondly because the model may not perfectly represent reality. However, with enough observations such that the underlying trends are captured by the model and if the optimum possible model is selected of the correct regression type, no significant variables are omitted and the regression assumptions are not violated then the standard error of the estimates should go some way to representing uncertainty in the data.

4. Model Selection

The ship's fuel consumption, RPM, draft (loading), degradation of systems (represented by time) and the environmental conditions (Beaufort number) are inextricably linked in a physical manner that is not immediately clear due to the often non-linear relationships between the various elements that make up the propulsion system. The condition of the hull, for example, depends on the age of the ship, the salinity and temperature of the water in which it operates, the hull cleaning schedule, the hull coating, the ratio of time spent at sea to time in port and the ship's speed. The fouling in turn affects overall ship resistance and is speed dependent because of the effect of the Reynolds number on the coefficient of friction. The subsequent relationship between fuel consumption (FC) and power incorporates deviations from a distinct fuel-speed law due to the varying specific fuel consumption, SFC (g/kWh) which is theoretically dependent on the combined propeller speed and engine load (adjusted for the shaft efficiency) and where on the engine layout diagram these variables coincide. These are in turn influenced by likely non-linear degradation effects (i.e. soot build-up in the engine) that occur over time. Another example is the Beaufort scale (BF) which is representative of the wind speed, one relationship between shaft power and wind speed, aerodynamic drag, can be approximated by a drag coefficient based on the transverse projected area of the ship perpendicular to the wind direction and the square of the wind speed [N. A. Hamlin and Sedat (1980)]. The principal effect of the recorded Beaufort number on fuel consumption however is actually the implicit effect of wind generated surface waves, one simplified relationship is based on the drag coefficient for wave resistance and the square of the wave height that is proportional to the ships power [(Lindstad, Asbjørnslett et al. 2011)]. However this only represents wind driven surface waves and does not account for swell. It also does not reflect the fact that the ship's speed may have to be reduced in heavy weather so as to not violate the maximum torque/rpm allowance of propulsion system components. The effect of BF will possibly cancel out due to its random directional nature however it is included in the analysis because of this interaction effect it has with speed and RPM.

So, although there is underlying theory to ship performance (in which only two examples of the many system interactions that exist are briefly highlighted above), the complexity of the interactions and the low level of detail with which the independent variables (e.g. environmental conditions) are recorded, means that statistical techniques can provide valuable insights into how changes in input variables independently and collectively effect performance. Furthermore, when applied to a dataset which features both measurement and aleatory uncertainty and a large enough sample, statistical analysis can produce a model which if close enough to the 'true behavior' of the system can form a baseline against which the magnitude of these uncertainties can be assessed.

In order to ensure that the model is as close as possible to the 'true behavior' of the system (the optimum model) the following method is applied to both the noon report data set and continuous monitoring data for each ship:

- Filter the data and remove outliers
- Test multicollinearity between independent variables
- Confirm the regression assumptions are not violated by assessing the residuals for independence, bias and normality
- Determine which predictor variables to include and which redundant variables to omit from the model

4.1. Filtering and Outlier Removal

Various techniques were applied to remove outliers which were identified by examining residuals and investigations following initial visual inspection of the raw dataset. The data is of course not filtered for weather in order to capture this influence in the regression model.

After the above procedure, ships with fewer than 45 observations were not included in the analysis because of the risk that the model becomes over parameterised and the p-stat is then only a rough and potentially unreliable approximation. A lower value is also unlikely to be able to sufficiently capture the trends in the data. This left 89 ships in the analysis.

4.2. Multicollinearity

The effect of collinearity is a matter of degree rather than a question of presence or absence [Paul (2008)]. 'Near linear' dependencies between the explanatory variables are problematic in the interpretation of the estimated parameters and their relative importance on the output variable; there may be a large standard error associated with the parameter estimates. However the adjusted R^2 value is still able to indicate the proportion of total variation in the data described by the model. The relevant adverse effect for this particular analysis is that neither of the coefficients of collinear variables will appear statistically significant when both are included in the model and therefore may be automatically excluded. Assessment of collinearity was quantified through the variance inflation factor (VIF). The threshold for presence of collinearity was VIF greater than 5. For 10 ships, speed and RPM were found to be collinear, in these cases it was confirmed that at least one or the other predictor was included in the resultant model.

4.3. Residual Analysis

The standardised model residuals should be independent, unbiased and normally distributed to ensure there is little information remaining in them. The residuals are tested for normality by the Jarque-Bera test of the null hypothesis that the residuals come from a normal distribution with unknown mean and variance. If the null is accepted then the t-table gives valid p-values and confidence intervals. In 26 cases the null was rejected however the application of a minimum threshold for sample size justifies the use of the t-table. The mean of the residuals was found to be very close to zero (to the order of 10^{-10}) for all ships. The Pearson correlation coefficient was used to test the linear correlation between the residuals and the predicted estimate, it was found to be of the order 10^{-10} for all ships, this confirmed the homoscedastic nature of the residuals and the efficiency of the least squares method. Finally, the correlation between residuals and each predictor variable is tested again using Pearson's correlation coefficient, no discernible correlations were found, although that does not discount systematic patterns based on higher order correlations. The predictors and residuals were plotted against each other and checked visually for a handful of ships. This is supportive evidence for the case that there are no omitted variables or reverse causation present.

4.4. Removal of Redundant Variables

There is a material but ambiguous difference in the variable interactions between ships due to differences in the environments in which they operate, their initial design characteristics and the physical degradation that affects the efficiencies of their various on board systems. The term 'degradation' is here used as a generic description for reduction in performance due to the combined effect of hull fouling, engine wear and/or propeller fouling/cavitation. Owing to the bespoke differences between individual ship performances, the model was defined separately for each ship by a backward elimination procedure. The full model included the explanatory variables; Speed, RPM, Beaufort number, time, loading and selected interaction terms. Predictors are then sequentially removed if the p-values of the coefficients are not significant.

5. Results and Discussion

5.1. Noon Reports

An example of the resultant regression model for one ship is shown in Table 1 and Table 2 (the fuel consumption – RPM characteristic is shown in Figure 1); in this case, this was formulated from 220 observations over a time period of 273 days. The predominant explanatory variable is log (RPM). In this instance ship speed as a main effect was included as a significant variable automatically because it is present in the interaction terms. As one would expect RPM, BF, time and loading all positively correlate with fuel consumption. The effect of time may perhaps be due to the aforementioned physical degradation in any of the on board systems, at higher speeds the impact on fuel consumption is exacerbated (positive $\beta 9$). Figure 2 shows the marginal effect of time on fuel consumption for the speed range, that is the increase in fuel consumption attributed to a 1 unit increase in time (per day), found from the partial differentiation of the fuel consumption with respect to time. From the figure it can be seen that if the ship's speed is 15knots then the total increase in FC over 200 days would be of the order of 25tpd (0.125 x 200). The main speed effect appears to be negatively correlated however because of the interaction terms the marginal effect of speed on fuel consumption is dependent also on time and BF and considering these also the correlation is positive. This shows how speed interacts with the other variables to effect fuel consumption and is found by the partial differentiation of the model with respect to speed.

Table 1: Regression of fuel consumption on ship speed, rpm, Beaufort number and loading (#23)

Predictor Variable		**'Unstandardised' Regression Coefficient, b**	**Standard Error**	**p-value**
Constant	$\propto$	35.032	0.189	7.74E-215
Log(Speed)	β_1	-0.073	1.456	9.60E-01
Log(RPM)	β_2	85.993	2.024	2.51E-98
BF	β_3	0.455	0.054	1.45E-14
t	β_4	0.243	0.117	3.89E-02
Loading	β_5	1.019	0.249	6.34E-05
V x BF	β_7	0.846	0.402	3.69E-02
V x t	β_9	0.071	0.014	1.01E-06

Table 2

Adjusted R^2	0.95
Confidence Interval, %	14.44
Standard Error, %	3.74

Figure 1 shows, for the regression presented in Table 1, the bars of standard error on the fuel consumption-speed relationship for this ship. This presents the match between the statistical model and the noon data and the magnitude of the error bars with respect to the actual fuel consumption. The implications of this are discussed in further detail later.

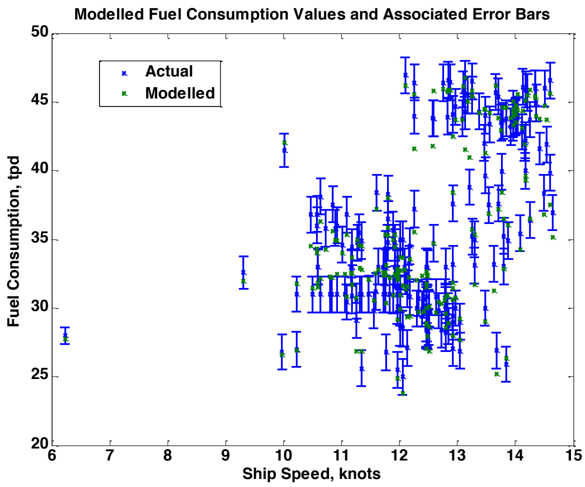


Figure 1

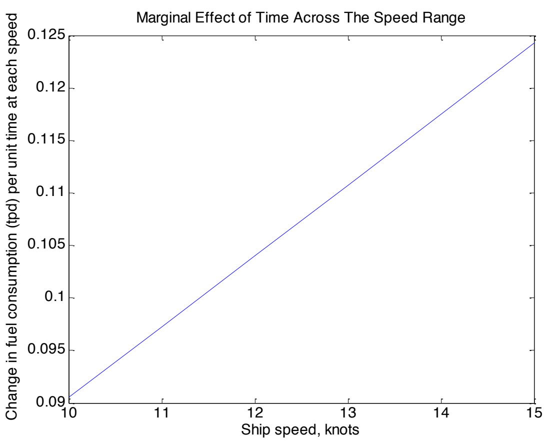


Figure 2

This procedure is applied to each of the 89 ships. Figure 3 shows the variation of the R^2 value between ships. A low R^2 value may be due to measurement or aleatory error from the data inputs as described in the introduction, there may be additional causes of the variability due to unknown or not measured effects for example the effect of swell on fuel consumption is not included in the BF scale and the wind direction is not recorded so extra drag due to side force and direct wind drag influences are not separated out. The R^2 is an indication of how well the model fits the data so if there are omitted variables or effects not accounted for then this is also reflected in R^2, the described method aims to reduce this possibility. Figure 3 shows on the right hand side the relative standard error for each ship as a percentage of the mean fuel consumption for that ship. This is between 1% and 8%.

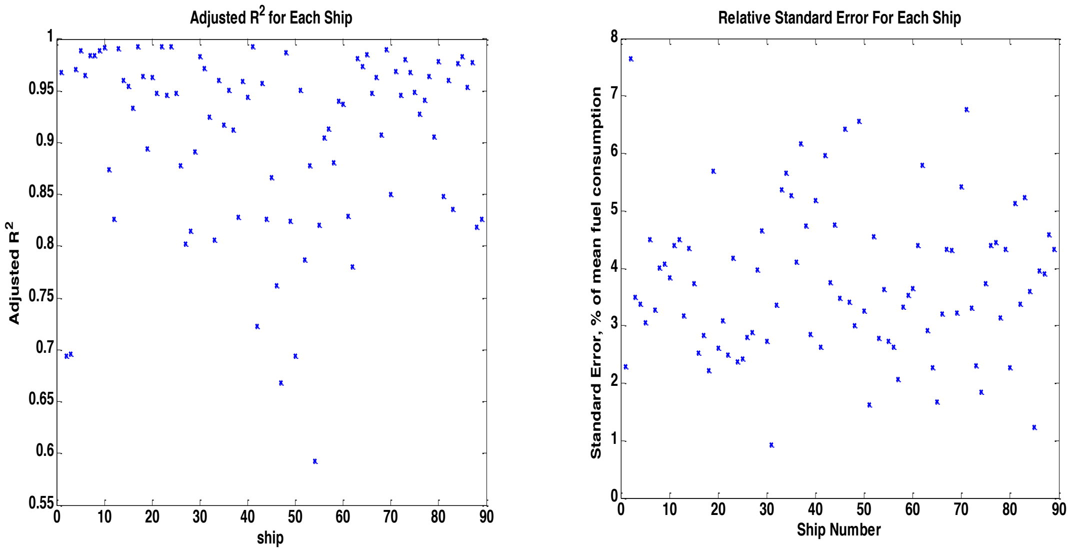


Figure 3

Figure 4 shows the variability in the total number and type of predictor terms remaining in the optimum model after the backward regression starting with the full model. These are arranged in order of the relative standard error, although there is no discernible correlation between this and the predictor terms. The distribution of frequency of the inclusion of each term showed the more prevalent use of log(RPM) and log(V), followed by BF, time and loading then the interaction terms were least frequently found to be significant.

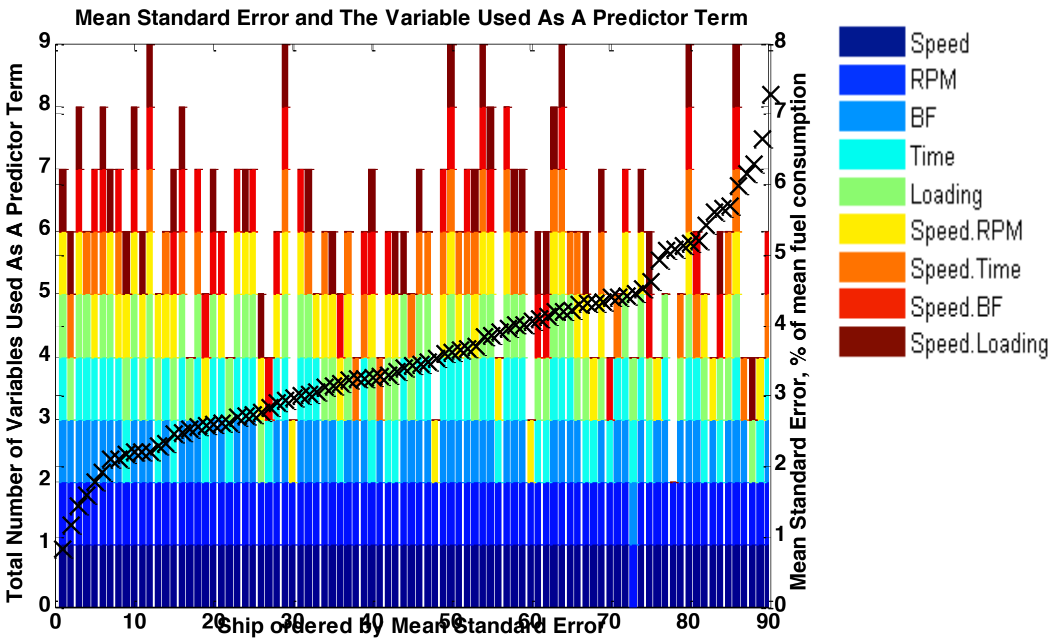


Figure 4

This noon data is for four different ship types, a comparison of the mean confidence intervals between the groups was made but no obvious relationship was seen.

Generally speaking the R^2 values are reasonably high (Figure 3) which implies that the underlying trends are captured by the regression models. This is supported by a scarcity of common features exhibited by ship models with high R^2 values, the lack of correlation between standard error and ship type, the normality and homoscedasticity of the residuals, the variation in the omitted and included variables and the magnitude of their coefficients. This provides evidence in support of the adequacy of the backward elimination method in reducing epistemic uncertainty and the utility of standard error as an indicator of the measurement and aleatory uncertainty.

5.2. Continuous Monitoring Data

Both continuous monitoring data and noon report data has been obtained for the same ship over the same 4 month time period. This data is shown in Figure 5. At some lower speeds (5 to 10 knots) the CM reported fuel consumption is quite high. This could be due to the 'vessel load', i.e. for the feed water heater. This requires steam from the main boiler when the ship's speed is insufficient to maintain the steam pressure through the turbine which would otherwise allow for excess steam to be siphoned off for this feed water heating purpose. This does not appear to be picked up in the noon reports, perhaps due to varying locations of fuel consumption sensors.

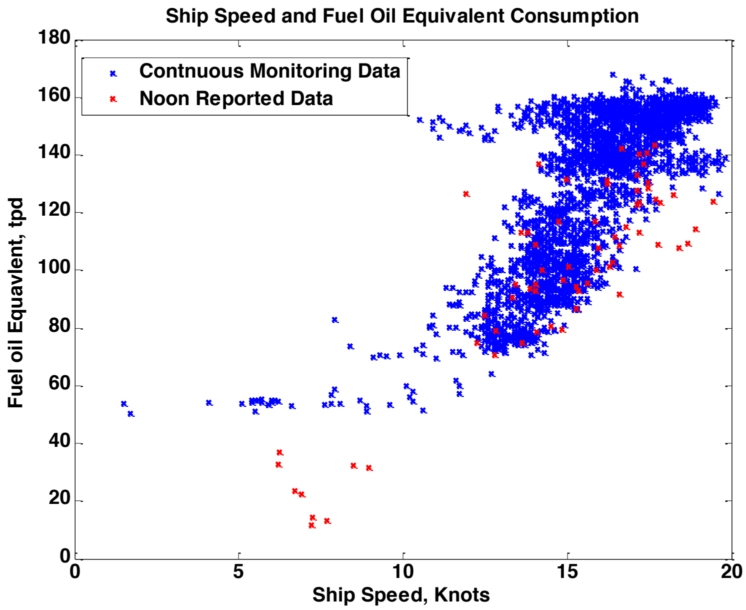


Figure 5

The regression analysis was applied to this CM and noon report data. The results are as in Table 3.

Table 3: Regression analysis of noon reported and continuous monitoring data for the same LNG carrier

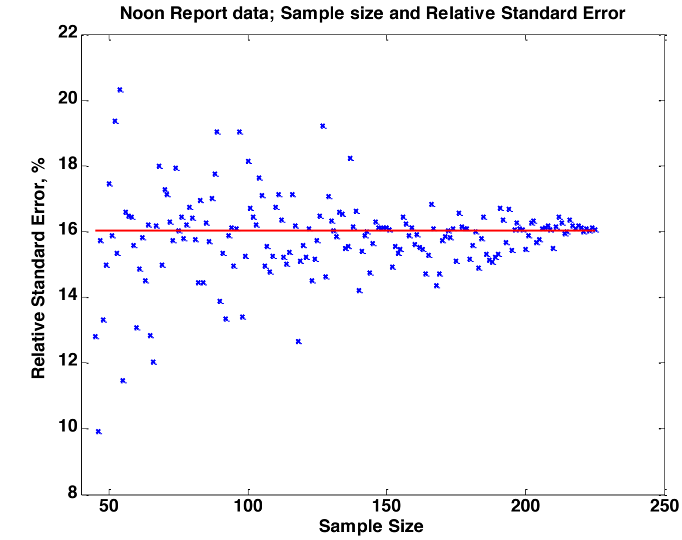
	Number of observations after outlier removal	Adjusted R^2	Relative Confidence Interval, % (95% level)	Absolute standard error, tpd	Relative Standard Error, %
Noon report data	205	0.88	61.39	13.38	15.80
Continuous monitoring	10633	0.95	18.19	5.97	4.64

The confidence interval and standard error derived from the noon report data of the LNG carrier are large relative to those of the oil tankers. This may be because of increased sources of uncertainty on LNG carriers owing to the presence of the steam power plant; it is more difficult to get an accurate measure of the gas and corresponding fuel oil equivalent that is burnt in a steam powered LNG ship. This depends however on the specific procedure involved in the measurement and on which component of the power plant the fuel sensor is physically located. The temperature and composition of the boil off gas used to derive the fuel oil equivalent mass may be assumed rather than measured and this may vary according to the grade/quality of the LNG cargo loaded, it is also possible that the composition of the boil off may vary throughout the voyage, particularly for the natural boil off.

There is a substantial reduction in the uncertainty when the CM data is used, this relates to, among other factors, the increased measurement variables that enable the gas composition, temperature, heating values and density to be recorded and therefore improve the accuracy of the gas consumption measurement and calculation of foe. This is specific to the LNG carriers and the magnitude of the reduction in uncertainty may not be extrapolated to other ship types. There are some characteristics of the CM dataset however that would enable improvement in the certainty generally; the many elements of human error described in the introduction will be eliminated, as well as the improved repeatability of measurements, limited only by the precision of the sensors. Extra data fields that the automation and therefore reduction in manpower allows for means that more refined data filtering techniques can be implemented. The presence of both wind speed and direction allows true wind speed to be calculated, and the numeric rather than binary draft input further reduces rounding errors and improves the uncertainty.

5.3. Sample Size and Standard Error

Aleatory uncertainty is omnipresent and cannot be reduced by increasing sample size. This was investigated by extracting random samples of increasing magnitude from each dataset. The results are presented graphically in Figure 6 for the CM and noon report dataset. In both cases it is seen that with small samples spurious data points either very close to or far from the regression line will cause the standard error to fluctuate. With sufficient observations the effect of these will become insignificant relative to the majority and the standard error will tend towards the mean standard error. The variation but not the magnitude of the measured standard error is reduced by increased sampling frequency, its distribution was also found to be normal about the mean. This supports the argument that it is aleatory uncertainty that is represented by the standard error and also acts as a means of ensuring that the sample size is adequate to make this assumption. If the time period is not of sufficient length to build a statistical model that represents reality then, when randomly selecting observations to construct samples of increasing magnitude, then the standard error will not fluctuate about a mean with a normal distribution owing to instabilities in the backward elimination procedure.



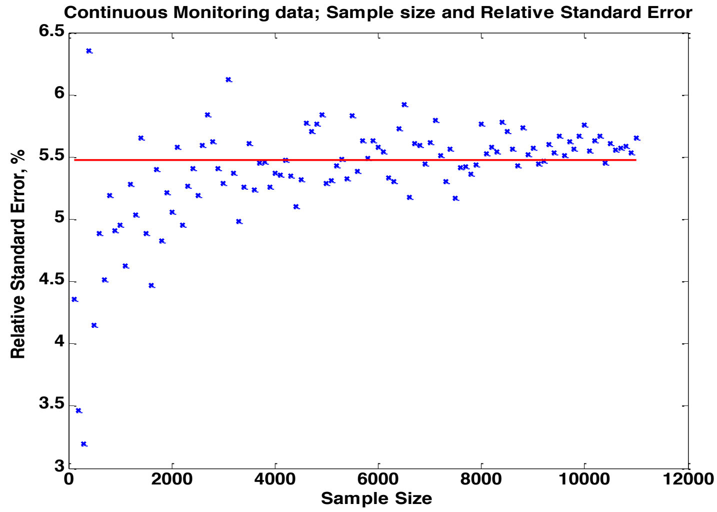


Figure 6: Sample size and relative standard error TOP: Noon report data, BOTTOM: CM data

5.4. Theoretical Comparison and Sample Size

Operational optimisation methods (for example, deciding when to clean a hull, or selecting ship speed) may be based on statistical models derived from historical data that primarily measure the change in fuel consumption, or the reduction in ship speed over time, due to some kind of ship degradation, i.e. hull fouling. Often the change is compared to some baseline condition. The significance of including the error measurement in the reported results is highlighted in the following by using a theoretical performance curve which, in the absence of sea trial data or an equivalent "clean hull" reference point, is estimated to be a representative baseline to the values of fuel consumption obtained using the statistical method defined above. This section also explores the use of the theoretical model in corroborating evidence from the statistical model to ensure that the epistemic uncertainty is minimised and the standard error is a true representation of the measurement and aleatory uncertainty.

For the baseline the calm water resistance was calculated from the empirical formulae by Holtrop and Mennen (1982) and the propeller efficiency and resultant RPM was calculated from the Wageningen B-series relationships derived by Oosterveld and Oossanen (1975). The two statistical model outputs are compared to the theoretical model firstly using a sample of data of the same overlapping time period (4months), this is presented in Figure 7 with the standard error for each represented by the error bars. Secondly, the dataset from the entire period for which there was data available (224 observations over approximately 18months)

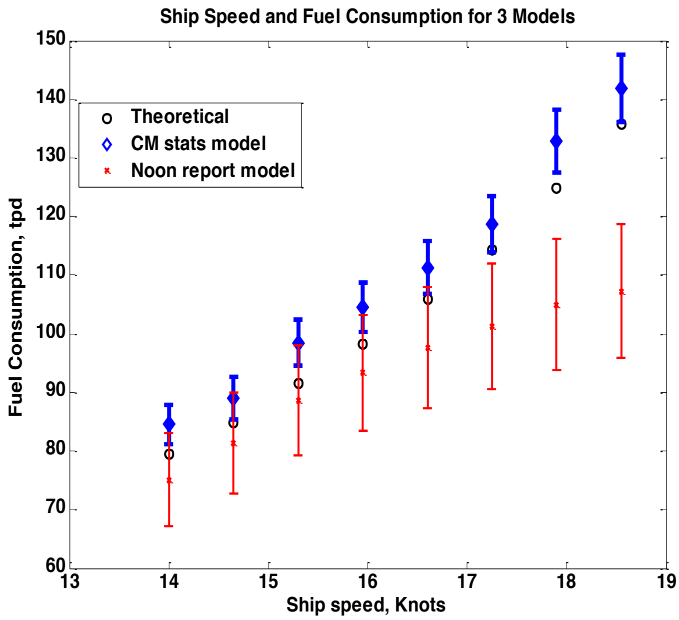


Figure 7

Figure 7 clearly indicates the greater uncertainty in the noon report dataset (9.76tpd absolute standard error) relative to the continuous monitoring data (5.97tpd absolute standard error). The agreement in the trend of the speed - fuel consumption relationship between the theoretical and the statistical analysis from the CM data builds confidence that the CM model's epistemic uncertainty is low.

The noon report data model and CM model overlap across the speed range 14-17 knots but agreement at higher speeds is poor. The similarity between theory and CM implies that the deviation of the NR model at higher speed is caused by epistemic uncertainty in the NR model. This was investigated further by expanding the time period for the noon data to 16 months. Figure 8 shows the result.

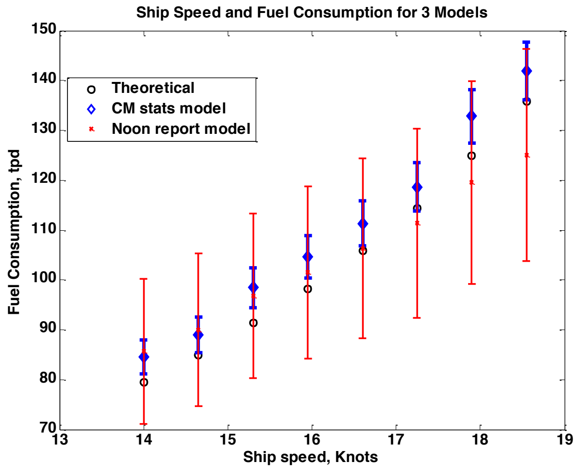


Figure 8

Although still underestimating the fuel consumption at higher ship speeds, the noon report model now corresponds more closely with the theoretical and CM models across the speed range. This suggests that the standard error (13.38tpd) is now a better representation of the measurement/aleatory uncertainty as the epistemic uncertainty has been reduced. This highlights the importance of corroborating with theory to cross check that the model does have some overlap with what is expected in reality, standard error as a measure of uncertainty is only meaningful if the epistemic uncertainty is low. If it is not a larger dataset over a longer time period can be of assistance. This may be a second method of ensuring that the sample size is adequate to justify the use of the standard error in representing the measurement uncertainty in the data (the first being to randomly select samples of increasing size and ensuring the standard error fluctuates normally about the mean as in section 5.3).

The continuous model shows a good match to the trend of the theoretical and the differences might be seen as a representation of long term degradation of the ship relative to its age plus shorter term effects due to fouling since the last hull scrub. The standard error bars however are important; if the optimum time to hull scrub or optimum speed is determined from a techno-economic model then the per cent error becomes significant and needs to be quantified and considered.

6. Conclusion

The numerous sources of uncertainty in noon reports have been described as well as the non-linear interactions both between on board ship systems and between the ship and its environment. This complexity has been investigated through the use of a multiple linear regression model to capture the underlying trends and to present the standard error associated with the fuel consumption. This produced a number of key findings:

6.1. The viability of statistical models

Statistical techniques and backwards regression were successfully applied to sets of noon reports for a number of ships. A multi linear regression model found by a backwards elimination procedure is applied to the noon reports from 89 tankers which has indicated that the relative standard error is generally in the range of 1-8% for various types of oil tanker. The equivalent values are higher for an LNG carrier (15.80%) which is possibly due to the nature of sensors and measurements specific to the different ship type and power plant.

The high adjusted R^2 values, lack of correlation between standard error and other features (in particular sample size) and the normality and homoscedasticity of the residuals implies generally that the statistical model captures the underlying data trends and is credible for use in performance analysis. Furthermore, the standard error is thought to be generally representative of aleatory and measurement uncertainty and it enables users to assess the level of certainty from which they can use the data and model to assess the ship's performance.

6.2. Assessment of dataset size

A method of ensuring that the sample size is adequate to justify the use of the standard error in representing the measurement uncertainty in the data is presented. If the dataset is adequately large then the following should not be violated:

- When samples of increasing size are randomly selected from the dataset the standard error should fluctuate normally about the mean
- There should be a degree of agreement in the trends described by the statistical model and the theoretical model to indicate low epistemic uncertainty and reduce the likelihood of omitted variables.

6.3. The use of statistical models for determining the relative significance of influences on fuel consumption

The deployment of regression with backwards elimination can be used to isolate the variables that influence performance and their relative significance. This is a useful source of information, particularly in conjunction with physics based models, as it can perform a validation of those models or be used to provide additional insights beyond those available through physics or statistical modelling alone.

6.4. The superiority of CM over NR

The data acquisition from an on-board continuous monitoring system yields a material reduction in the uncertainty; the standard error is 4.64%. It cannot be said if the magnitude of this decrease can be extended to other ship types which have a lower existing uncertainty. This will depend on the quality of the noon reported data in terms of the range of variables included, the accuracy and repeatability of the measurement instruments and their maintenance and calibration procedures, the resolution of the measure and the stringency with which reporting procedures are compiled and subsequently adhered to by the crew; these factors vary also depending on the operator.

6.5. Uncertainty in the context of energy efficiency and fuel saving claim's assessment

The practical implications of the varying degrees of uncertainty in the dataset have been briefly described with regards to assessing historical data analysis for operational optimisation tools, i.e. hull maintenance schedules or optimum speed models and for their potential in assessing the performance of interventions such as a new hull coating type. The use of noon data and continuous monitoring data in this way is compared to help answer the question "Is the model reliable enough for the purposes with which its use is proposed for?

There are a multitude of technological products and operational support tools on the market that advertise fuel savings. Regardless of the method of data collection, there will always be some standard error (aleatory uncertainty at the least is omnipresent) and this is not always obviously reported. It is perhaps interesting to see that the best case addressed in this paper (on board CM equipment) indicates there could be an error of 4.6% associated with the fuel consumption measurement.

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