Evaluation of Ship Energy Efficiency Predictive and Optimization Models Based on Noon Reports and Condition Monitoring Datasets

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Abstract - **For a long time, the shipping industry has relied on Noon Reports to extract the main parameters required to define both the ship's performance and fuel consumption, despite the fact that these reports have low sampling frequency (approx. 24 hours. Nowadays, satellite communications, telemetries, data collection, and analytics are making possible to treat a fleet of ships as a single unit. Thus, the shipping industry is definitely part of the information business. In the current work, we present a qualitative and quantitative comparison between the models developed from historical trends that are extracted from Noon Reports and the Continuous Monitoring System. The analysis is based on parameters that are reported by both data sources. While effort has been made in order to quantify variances due to the different sampling rate, our main focus was on quantification of uncertainty and the resulted confidence interval in order to clarify the potential and limitations of the resulting predictive models. The paper aims to contribute to the areas of tools and mechanisms of data analytics, in the specific area of maritime intelligence.**

Keywords - Continuous Monitoring; Noon Report; Performance Assessment; Trim Assessment.

I. INTRODUCTION

Today's ships are equipped with numerous sensors and advanced systems which help to operate vessels more efficiently. Any decision making inside a shipping company must be based on accurate and verifiable data and not just on feelings, instincts, or intuition. Managing a fleet of vessels involves complex processes. The ability to utilize data to obtain actionable knowledge, predictions and insights allows for continuous process improvements and optimal performance throughout the lifetime of assets.

The ability to manage all data and information from different systems onboard in a safe and efficient manner enables a new level of possibility to analyze and monitor situations, critical operations and adverse conditions as well as to increase performance awareness. Integration of performance indicators across systems is vital for getting the full overview of actual asset operation. Aggregation of lower level performance indicators into top-level Key Performance Indicators (KPIs) is a proven approach to performance management as the condition and operation of sub-systems is crucial for the total system operational predictability and the need for maintenance. Knowing how the vessel and its systems perform in real operation is a cornerstone for optimizing the fuel efficiency and technical maintenance of the vessel and its systems.

Aldous [1] provides a comprehensive review of the recent developments in performance monitoring based on data derived either by Noon Reports or by Continuous Monitoring System. In this work, an extensive review of the models, namely theoretical, statistical and hybrid used in ship performance assessment is provided. Additionally, the author refers to eight categories of application of ship performance models: *i)* Operational real-time optimization (e.g Armstrong [2], Psaraftis & Kontovas [3]), *ii)* Maintenance trigger (e.g. Walker & Atkins [4]), *iii)* Evaluating technological interventions (e.g. Stulgis [5]), *iv)* Operational delivery plan optimization (e.g. Rakke et al. [6]), *v)* Fault analysis (e.g. Spandonidis & Giordamlis [7], Djeziri et al. [8]), *vi)* Charter party analysis, vii) Vessel benchmarking (e.g. Bazari [9]) and *viii)* Inform policy (e.g. Smith et al. [10]). In that framework, Aldous et al. [11] provide a method for quantifying the uncertainty in reported fuel consumption 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 onboard continuous monitoring system. Furthermore, ISO [12] describes the uncertainty entered into the measurement from various sources as well as proposes a data handling methodology. Nevertheless, utilizing data from ships in order to support the decision-making process of shipping companies, and to provide insight for cost-efficient operations, is not a new idea. This has been previously mentioned as part of traditional methods based on Noon Reports data, which are quite popular within the marine industry.

In the current work, we take the first step towards quantifying the statistical trustworthiness of different methods of data collection, as obtained by Noon Reports (NR) and from LAROS Continuous Monitoring System (L-CMS). Our aim is to examine the capabilities of each method to provide reliable input in performance assessments, by presenting a case study based on real obtained datasets from NR and L-CMS.

The rest of the paper is structured as follows. In Section II, we present briefly the basic architecture of the LAROS Continuous Monitoring System. In Section III, verification, validation, and software modules of the L-CMS platform are presented. Test results and corrective actions taken are also discussed. In Section IV, we present the methodology used in the current work for the quantification of performance based on a standard indicator as well as the tested ship and methods of data acquisition. Statistical measures for the quantification of the reliability level of each method are utilized. A study on how differences in the frequency of the reporting could affect trim optimization is also included. Finally, in Section V, we discuss the key results of the study.

II. SYSTEM DESCRIPTION

For the Continuous Monitoring System, we relied on LAROS system.

- Smart Collectors are connected using the appropriate interface to analog or digital signals coming from different sensors and instruments of the vessel.
- Smart Collectors analyze the signals and calculate the required parameters. The sampling rate, as well as the rate of the parameters calculations, can be set from 100 msec up to 30 minutes.
- Smart Collectors set up a wireless secure network inside the vessel to transmit the processed data to the Gateway with a user-defined sampling rate and ability to maintain and customize them remotely. The wireless protocol is based on IEEE 802.15.4 MESH (Adams [13]) with additional layers and data format to cover the requirements of the vessel environment and increase the network Quality of Service.
- Through the Gateway, all the measured and processed parameters are stored in Central Server (onboard). The Server periodically produces binary files and compresses them in order to reduce the size of the data to be sent via normal satellite broadband.
- The compressed files are transmitted through File Transfer Protocol (FTP) to the HQ database.
- In the data center, there is a service that decompresses the incoming files and stores the new measurements in the main database.

TABLE I. INDICATIVE FUNCTIONAL MODULES - SHIPPING

Module	***Needed signals***	***Connection points***
Propeller – Hull Performance	Vessel Speed, Shaft Revolutions per Minute (RPM), Shaft Power.	Speed log, Torque-meter- RPM Indicator.
Engine Performance	Fuel Oil Consumption (FOC), Power (Specific Fuel Oil Consumption - SFOC), Diesel Generator (DG) Output	Flowmeters [Fuel Oil (FO) flow], FO temp, FO density, DG Power Analyzer
FO Consumption	FOC, Vessel Speed through water, Shaft RPM, Boiler Status	Flowmeters (FO flow), FO temp, FO density, Boiler status indicator
On-line bunkering	Tank level, FO temperature	Cargo Control Console, Engine Control Room (ECR)/ Cargo Control Room (CCR) Indicators.
Maintenance managementt	Pressures, Temperatures, Alarms from critical systems	Alarm Monitor System (AMS), ECR Indicators
Power management	DG Output, Reefers Power Consumption	DG/Reefer Power Analyzers
Environmental conditions	Wind speed & direction, Water depth, Ambient temperature & Pressure	Anemometer, Echo-Sounder, weather station
Operational profile	Ground Speed, Drafts, Trim, Rudder angle	GPS, strain gage, Inclinometer

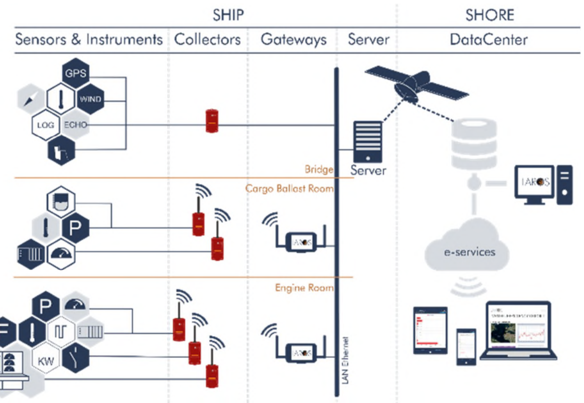

Figure 1. Operational data flow

Table I summarizes the main functionality modules, the needed signals, and the collection points onboard. In Figure 1, the aggregation of data needed for indicative functional modules is schematically illustrated.

III. SOFTWARE (SW) SYSTEM TESTING

The test plan followed can be briefly described as follows:

A. SW Module Verification

In order to verify our results, that is, to ensure that the code runs correctly given the equations of the model, two kinds of reliability tests were performed:

a) Evaluation of conservation principles and the subsequent execution of SW algorithms;

b) Monitoring of the systematic and the statistical error.

B. SW Validation

SW validation should involve comparison of characteristically obtained results with the same data obtained by other systems or sensors. However, there was lack of data during the implementation phase, as the vessel was at port/berth and main systems were inactive. In addition, Trim/List sensor was not mounted. To overcome this difficulty, two different kinds of validation tests were performed by different testing groups:

a) Regression testing. This represents the evaluation of data quality in the long term. The crew was instructed to report daily both LAROS measurements and sensor measurements of critical systems. Measurements were noted on regular periods (e.g. every 3 hours). Regression models (linear) were applied in order to estimate any deviation.

b) Performance testing. Performance testing was done by performing system and regression testing with a smaller sampling rate during both transient and steady-state conditions.

C. Test results

Testing procedure was performed according to the initial plan. Minor difficulties faced during the process were resolved ad hoc. The calculated uncertainties are standard deviations of the average (e.g. Speed over ground, Torque, etc.) at a 95% confidence level. The software module performs very well with a standard deviation of less than 1% in the steady state. Furthermore, for transient state validation showed the deviation of measured results from experimental data is less than 2%. This deviation was judged to be of acceptable level and is mainly caused by the sampling rate (60 sec) of hardware equipment. During the test period, based on data measured by the crew, onboard support engineers identified that main engine's fuel oil temperature presented a nonlinearity compared to actual measurements. Figure 2 presents some samples of the collected data: The issue resolved upon calibration of the collector with the appropriate linear function. Table II summarizes the results of system testing.

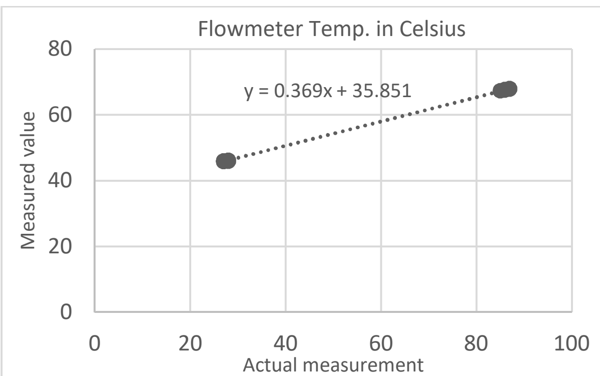

Figure 2. Correction factor and offset for the calibration of hardware

TABLE II. RESULTS OF SYSTEM TESTING

Test Case	*Pass/Fail*	*Deviation*
Conservation Principles	Pass	Deviation <0.5%
Statistical error	Pass	Reproducible averages within statistical uncertainties
Systemic error	Pass	Different OS Different web browser
Steady state	Pass	N/A
Transient state	Pass	N/A

IV. METHODOLOGY AND CASE STUDY RESULTS

We focus on a time period of 9 months for the performance assessment of hull and propeller, targeting mainly hull fouling degradation. The ship that provided the data for the comparison study is a 170000 DWT Bulk Carrier. In a first instance, we choose to use average values per hour from the L-CMS. The ship sailed about 60.5% of the considered time.

A. Evaluation based on power deviation

The targeted performance indicator is the increase of the required power, which affects significantly the ship's fuel consumption. The performance indicator is calculated as (ISO [12]):

$$\%Power\ increase = \frac{P_{measured} - P_{expected}}{P_{expected}} \quad (1)$$

where $P_{expected}$ corresponds to the expected delivered power needed to maintain a given speed at a specific loading condition and with no effect from environmental conditions. For the estimation of the expected power, we use as a model the reference power – speed curves obtained from sea trials, corresponding to the ballast and full load condition. We apply a correction on the power values for displacement deviation of the actual values from the reference ones using the Admiralty formula, according to the next equation:

$$P_{\mathrm{e}} = P_{\mathrm{e(ref)}} \left(\frac{\Delta_{act}}{\Delta_{d(ref)}}\right)^{2/3} \quad (2)$$

Furthermore, no extrapolation of speed-power curves is allowed, thus we utilize data only for the speed range of the trial tests. In addition, we are not considering measurements that correspond to values of displacement and trim that deviate more than 5% Δ and 0.5% L_{BP} from the respective values of the reference conditions. Furthermore, the performance index presented before is calculated by filtering data that exceeds various upper bounds of wind force (e.g. 4 Beaufort Force (BF), 5 BF etc.).

Different data acquisition methods are available for carrying out the assessment. The first is based on NR filled out by the crew on a daily basis and the second one relies on the L-CMS, in which several reporting frequencies have been examined (hourly, 15 and 5 min). We test the capability of the trend prediction over time using the 2 methods. The key idea for this comparison study is to use a fraction of the available information as hindcast data and the remaining period to play the role of the forecast period. The first three months are used as the hindcast period. The forecast trend is calculated based on hindcast (or trained) data using a linear regression model. The actual trend is calculated by the known data of the "forecast" period using the same model. In the framework of this study, we assume that the linear regression model is capable of providing the trend, as we focus on the comparison between the 2 methods.

Figure 3 shows the results when an upper bound of wind force of 5 BF is applied. In order to quantify the comparison between the actual and the forecast trend, we calculate the standard error of the estimate for the "forecast" period and we average over the whole wind force range (Figure 4). In this graph, we have also included the respective values of the various reporting periods. As expected, the frequent periods result in smaller estimate errors for the forecasting period.

 ISBN: 978-1-61208-681-1

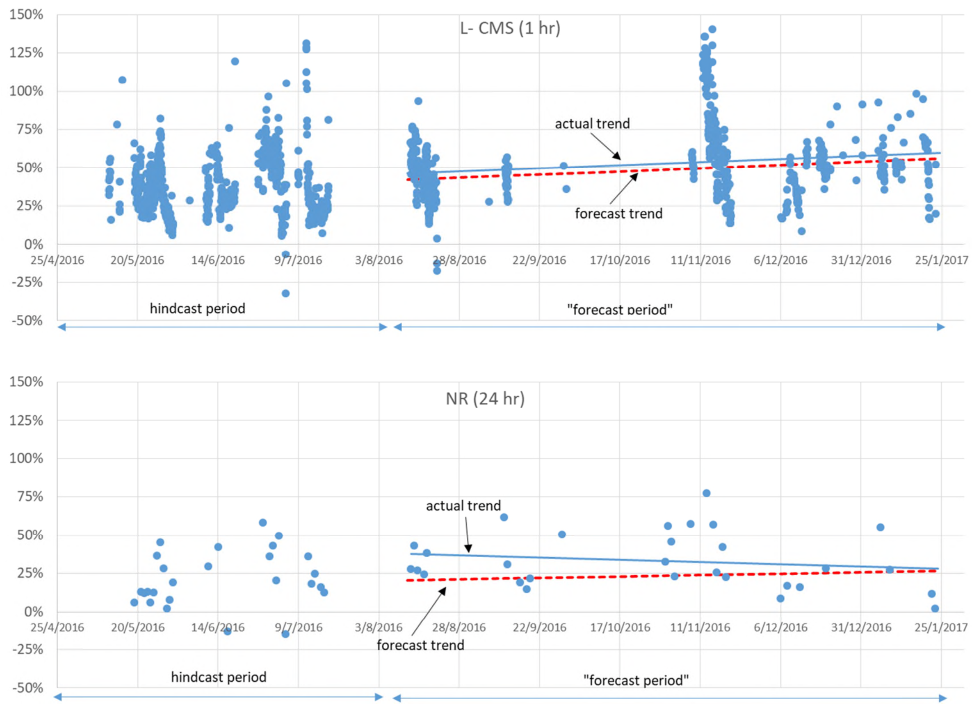

Figure 3. Actual and forecast trend for the CMS (upper graph) and NR (lower graph) methods for wind force lower than 5 BF.

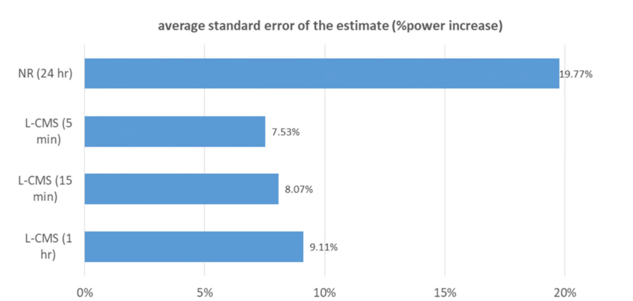

Figure 4. Sensitivity of the reporting periods on the average standard error of the estimate.

B. *Trim optimization based on Heickel coefficient*

Trim is defined as the difference between the draughts at ship's aft and forward, with positive trim to the aft. Being one of the usual methods for improving ship performance and energy efficiency optimization, trim optimization refers to minimization of the required power at vessel specific displacement and specific speed, thus reducing the hull resistance and/or increasing the total propulsive efficiency. Normally, the procedure demands dedicated model tests and/or computational fluid dynamics (CFD) modeling [14]. Next, we are using a traditional and reliable measure for the assessment of the hull and propulsion efficiency, such as the well-known Heickel coefficient that reflects the hydrodynamic efficiency of ship's hull form [15] in order to evaluate the ability to optimize the trim based on L-CMS and NR data. Heickel coefficient is defined as:

$$Heickel\ Coef. = V \cdot \left(\frac{\sqrt{\Delta}}{P}\right)^{1/3} \tag{3}$$

where Δ is the displacement, P the engine power, and V the ship's speed. Figure 5 illustrates Heickel coefficient propagation for the 9-month period under evaluation.

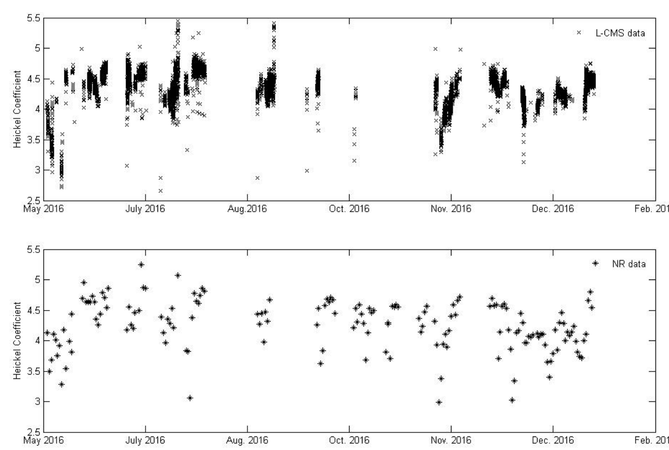

Figure 5. Heickel Coefficient propagation for L-CMS (up) and NR (down) data.

In general, the Heickel coefficient is operational speed and displacement dependent. In order to overcome this dependence, we evaluate the coefficient against the Froude number given by the equation:

$$Fn = \frac{V}{\sqrt{g \cdot L_w}} \qquad (4)$$

where g is the gravity acceleration and L_w is the ship's waterline length. Figures 6 and 7 illustrate the contour plots for Heickel coefficient with respect to Froude number and trim distributions for ballast and full load condition, respectively. The same filters and operational conditions were used for both cases (L-CMS and NR). Visual evaluation of the plots produced by L-CMS data (up) and NR data (down) prove that the limited number of sampling point from the latter make it almost impossible to produce any constructive result. In contrast, the plurality of data acquired from the former gives a good navigation map for delicate trim optimization. As shown, Heickel coefficient is directly related to trim, hence optimal trim with respect to the Froude number should be selected in order to reduce ship resistance.

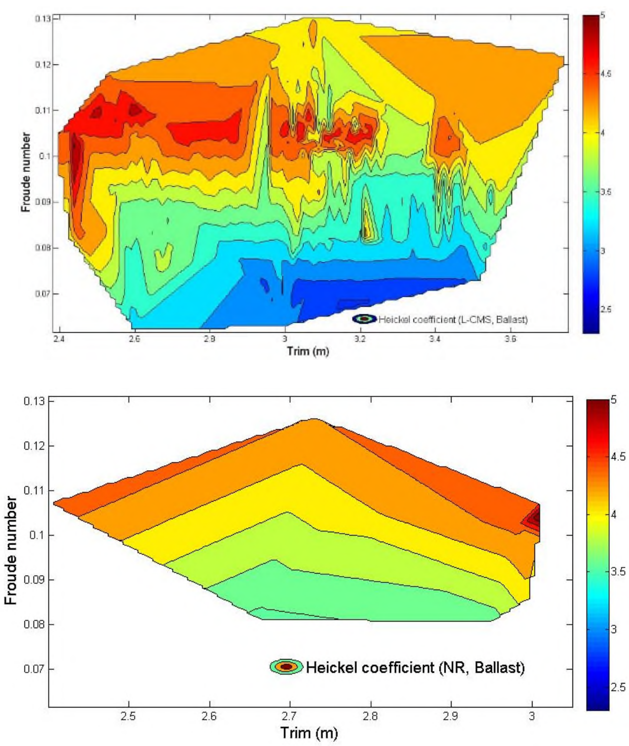

Figure 6. Heickel coefficient distribution vs Froude number and trim for ballast condition. L-CMS (up) and NR (down) data.

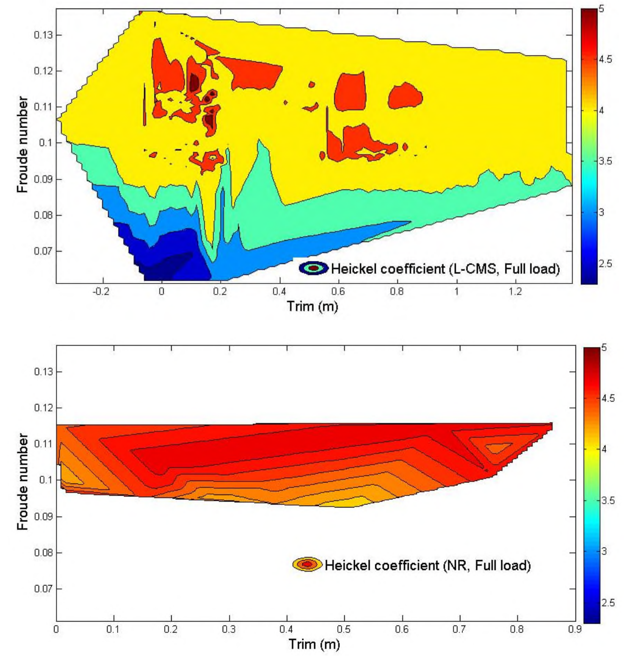

Figure 7. Heickel coefficient distribution vs Froude number and trim for full load condition. L-CMS (up) and NR (down) data.

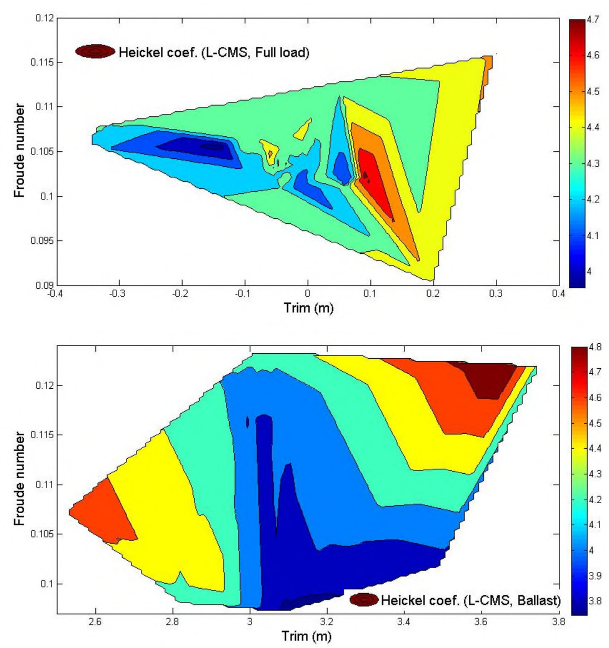

Figure 8. Heickel coefficient distribution vs Froude number and trim for ballast (up) and full loading (down) condition for wind force below 2 BF.

TABLE III. INDICATIVE FUEL GAIN

Loading condition	*Froude Number*	*Fuel reduction*	*Potential profit ($) for 20 days trip*
Ballast	0.12	1.3%	4.400
Ballast	0.1	2.6%	8.800
Full load	0.105	4%	16.600
Full load	0.1	3.4%	14.000

Working in that direction and based on L-CMS data, we evaluated the potential gain of trim optimization for specific operational conditions. Thus, we considered only data for wind force below 2 BF and Froude number between 0.09 and 0.125, which proved to be the normal value limits for normal operation. Figure 8 illustrates the contour plots for trim values with respect to Heickel coefficient and Froude number distribution for ballast (up) and full load (down) conditions. As shown in both cases and for Froude number close to 0.105, a correction to the trim value of the order of half a meter may result in a 4% reduction of fuel consumption. Table III presents some indicative results for the estimation of fuel and cost reduction on the assumption of half meter trim correction from ordered trim.

V. CONCLUSION AND FUTURE WORK

A step towards the assessment of the trustworthiness level of different data collection methods used in performance assessments was presented. For the current work, we restricted our efforts only to parameters that are reported by both sources: Noon Reports and LAROS Continuous Monitoring System. Power increase (%) was used as an evaluated performance indicator, while a trim assessment study was also carried out. Special attention was given to the quantification of our comparison study and especially to the frequency of the reporting period by examining the capability of prediction potential through the standard error of the estimate in each case.

The results indicated that NR data provide less statistically reliable data than the L-CMS. Of course, this depends also on the quality of the NR, which according to our analysis, in this specific case was quite sufficient. It is also derived that the high-frequency data of the L-CMS method provide a more detailed insight, as shown in the trim assessment study.

A logical next step in our research would be the systematic evaluation of the impact of the sampling rate on energy/emissions efficiency and key performance indicators, as well as of the learning procedure of predictive algorithms.

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