Proceedings of the ASME 2017 36th International Conference on Ocean, Offshore and Arctic Engineering
OMAE 2017
June 25-30, 2017, Trondheim, Norway

OMAE2017-61031

DATA-DRIVEN REAL-TIME DECISION SUPPORT AND ITS APPLICATION TO HYBRID PROPULSION SYSTEMS

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ABSTRACT

This paper describes a method for providing real time decision support based on measurements rather than optimizing a mathematical model. The proposed method is thus beneficial for systems for which the modelling would be inaccurate, the dynamics and complexity of the system would make it difficult to optimize in real time, or the risk of returning local minima is not acceptable.

The proposed method is implemented on four fishing vessels. These vessels are complex and give the skipper many choices related to how the vessel is operated. The developed tool advises the crew on in real time on operational decisions, particularly on the use of various diesel electric and diesel mechanic propulsion modes, including decisions such as the use use of shaft generator, direct coupling between main engine and propeller or not, propeller pitch, etc. This will presumably reduce both fuel consumption and emissions of CO2 and NOX.

Some examples of obtainable results from both onshore analyses and the onboard application are presented to demonstrate the methods applicability.

NOMENCLATURE

c The operational cost.
$\hat{c}$ The normalized operational cost.
$\hat{f}_c$ The function for normalizing operational cost.
n_s The number of solution candidates stored for each combination of operational demands.
n_x Dimension of $\boldsymbol{x}$. $n_x = n_{xc} + n_{xd}$.
n_{xc} Dimension of $\boldsymbol{x_c}$.
n_{xd} Dimension of $\boldsymbol{x_d}$.
n_y Dimension of $\boldsymbol{y}$.
$\boldsymbol{x}$ Operational choices, $\boldsymbol{x} = \left[\boldsymbol{x_c}^\intercal \ \boldsymbol{x_d}^\intercal\right]^\intercal$.
$\boldsymbol{x_c}$ Continuous operational choices.
$\boldsymbol{x_d}$ Discrete operational choices.
$\boldsymbol{y}$ Actual system output.
$\boldsymbol{y_d}$ Desired system output.
$\boldsymbol{x}_{\text{opt}}(\boldsymbol{y_d})$ The optimal decision for a desired system output.
$\boldsymbol{x}_{\text{bsf}}$ Evaluated approximation to $\boldsymbol{x}_{\text{opt}}$.
$\mathcal{X}_D(\boldsymbol{y_d})$ The set of candidate solutions for a specific system output.
$\hat{\mathcal{C}}_D(\boldsymbol{y_d})$ The set of normalized costs for the candidate decisions.
$\mathbb{R}$ The set of all real numbers.
$\mathbb{Z}$ The set of all integers.

INTRODUCTION

Operational efficiency is important for a range of industries and applications. The task of finding optimum operational choices in a complex process belongs to the discipline *operations research* [1]. The application of advanced analytical methods to solve the decision problem can improve the profitability or some other performance indicators significantly [2]. Several methods may be applicable, such as numerical optimization of a system model (like model predictive control [3] or mixed integer programming [4]), the use of neural networks [5], or developing a

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mathematical model able to directly estimate the best operational choices as a function of desired output. Skjong et al. [2] proposed using mixed integer linear programming as a suitable strategy for optimal unit commitment in ship power systems. Seenumani et al. [6] exploited time scale separation and a simplified dynamic model of the power system to achieve real-time optimization.

Fishing vessel operations can be affected by a large variety of conditions and operation modes. When this is combined with complex and flexible energy systems, finding the most energy efficient operational decisions can be challenging. These decisions are today based on experience, expectations of the near future and sound operational judgement. Energy audits performed by Basurko et al. [7] indicate that the energy consumption is largely impacted by engine conditions and use patterns. Even though a skipper may utilize their knowledge in operating the vessel, there may still exist configurations chosen in the past that yielded better performance. An analytical method that can utilize knowledge about the vessel is a valuable tool when making these operational choices. Modern ocean-going fishing vessels can be highly complex, one-of-a-kind machinery, and the operational profiles are also complex and changing with time. This makes it difficult and expensive to base an operational decision support system on mathematical models. Real time measurements are, however, often easily accessible, because of their high level of instrumentation.

Utilization of on-board time series measurement has also previously been applied to statistical analysis of ship performance under various sea states [8] and for preventive maintenance [9]. The present work is carried out in the research project Pursense [10]. This is based on the research project IMPROVEDO [11], which aimed to gain insight and improve vessel design and operation through the development of decision support tools and collection of operational data from fishing vessels.

Contribution

This paper proposes a method that may be beneficial in cases where the system is complex and difficult to model with sufficient fidelity for real-time optimization. The presented method uses long-term measurements as a basis for keeping an overview of how similar situations have been solved in the past, and then recommends the best known solution amongst these. This method is able to tell both how well the system performs in the current situation, as well as which actions should be taken to improve the performance.

GENERAL METHOD

Problem Formulation

Let $\boldsymbol{x_c} \in \mathbb{R}^{n_{xc}}$ and $\boldsymbol{x_d} \in \mathbb{Z}^{n_{xd}}$ denote continuous and discrete decision variables, respectively. The mapping from inputs to outputs are declared by $\boldsymbol{y} : \mathbb{R}^{n_{xc}} \times \mathbb{Z}^{n_{xd}} \to \mathbb{R}^{n_y}$. We regard the system under consideration to be in steady-state conditions. This means that we assume that the mapping from system input to output does not have any dynamics, meaning that it is not time dependent. Suppose the desired system output is $\boldsymbol{y_d}$, also denoted operational demands. Our objective is to find an element in the set of constrained decision vectors that minimizes some scalar cost function $c : \mathbb{R}^{n_{xc}} \times \mathbb{Z}^{n_{xd}} \to \mathbb{R}$, and at the same time ensures that the desired output $\boldsymbol{y_d}$ is obtained. Define the n_x-dimensional vector $\boldsymbol{x} := \left[\boldsymbol{x_c}^\top \ \boldsymbol{x_d}^\top\right]^\top$ and the constrained sets $\mathbb{X} \subset \mathbb{R}^{n_{xc}}$ and $\mathbb{D} \subset \mathbb{Z}^{n_{xd}}$. Our optimization problem can be stated as:

$$\begin{aligned} \arg\min_{\boldsymbol{x}} \quad & c(\boldsymbol{x_c}, \boldsymbol{x_d}) \\ \text{s.t.} \quad & \boldsymbol{y}(\boldsymbol{x_c}, \boldsymbol{x_d}) = \boldsymbol{y_d}, \\ & \boldsymbol{x_c} \in \mathbb{X}, \\ & \boldsymbol{x_d} \in \mathbb{D}, \end{aligned} \tag{1}$$

where $\mathbb{X}$ is a compact convex set and $\mathbb{D}$ is the set of possible values for the discrete decision vector. Note that there may exist several decision vectors that give the same minimal cost and that satisfy the constraints of the optimization problem. Let the set of optimal decision vectors for a given $\boldsymbol{y_d}$ be defined as $\mathcal{X}^\star(\boldsymbol{y_d})$. An essential challenge when trying to solve this problem is that we do not have expressions for neither the cost function $c(\boldsymbol{x_c}, \boldsymbol{x_d})$ nor the output function $\boldsymbol{y}(\boldsymbol{x_c}, \boldsymbol{x_d})$.

Method Description

The approach for solving Eq. (1), where we do not have explicit definitions for c and $\boldsymbol{y}$, is based on the application of long-term time series measurements of the operation under consideration. All the historic data form our basis for decision making. Let $\boldsymbol{x}_{\text{bsf}}$ be a decision vector that has given the minimal cost for a specific desired output $\boldsymbol{y_d}$ in historic operations. We assume that the historic operations spans a space of operational choices rich enough to include the optimal solution to Eq. (1). Therefore, an approximate solution to Eq. (1) with the corresponding cost is

$$\boldsymbol{x}_{\text{bsf}} \approx \boldsymbol{x}_{\text{opt}} \in \mathcal{X}^\star(\boldsymbol{y_d}), \tag{2a}$$

$$c_{\text{opt}}(\boldsymbol{x}_{\text{c,opt}}, \boldsymbol{x}_{\text{d,opt}}) \approx c_{\text{bsf}}(\boldsymbol{x}_{\text{c,bsf}}, \boldsymbol{x}_{\text{d,bsf}}). \tag{2b}$$

A typical use case may be situations where $\boldsymbol{y_d}$ changes over time. For this reason, a decision support system would need to resolve Eq. (1) whenever $\boldsymbol{y_d}$ changes. If one imagine an optimal cost surface as a function of $\boldsymbol{y_d}$, this surface can be highly nonlinear. The nonlinearity can be due to parameter sensitivity in the optimization problem formulation. In other words, a small change in $\boldsymbol{y_d}$ can give a large change in the optimal cost c_{opt}.

If an application uses the approximate solution from Eq. (2), the above mentioned characteristics make the solution prone to error due to two effects.

1. $\boldsymbol{x}_{\text{bsf}}$ is based on a set of situations where $\boldsymbol{y}(\boldsymbol{x}) \approx \boldsymbol{y_d}$. This is because the historic operational demands are based on measured values where uncertainties are inevitable.
2. When given a desired $\boldsymbol{y_d}$, interval aggregation around $\boldsymbol{y_d}$ is performed to retrieve the necessary amount of historical data to find $\boldsymbol{x}_{\text{bsf}}$.

In an attempt to mitigate these challenges, we can reformulate the optimization problem to minimize a normalized cost $\hat{c}$ instead of the original c. The motivation for a normalized cost is to reduce as much as possible its sensitivity to changes in the operational demands $\boldsymbol{y_d}$. We propose a normalized cost that depends on $\boldsymbol{y_d}$:

$$\hat{c}(\boldsymbol{x_c}, \boldsymbol{x_d}, \boldsymbol{y_d}) := \frac{c(\boldsymbol{x_c}, \boldsymbol{x_d})}{\tilde{f}_c(\boldsymbol{y_d})}, \tag{3}$$

where $\tilde{f}_c(\boldsymbol{y_d})$ is an approximation of the total cost given a particular operational demand. This normalization makes it easier to compare the optimal cost for variations in $\boldsymbol{y_d}$. Later we will see that this normalization is useful when comparing costs within a neighborhood of $\boldsymbol{y_d}$.

In its simplest terms, the objective of the decision support is: "Our desired system output is $\boldsymbol{y_d}$, what is $\boldsymbol{x}_{\text{opt}}$?" We propose an algorithm that uses the historical data as a basis for solving Eq. (1). It consists of two distinct processes:

1. Keeping track of and updating the best historic solutions $\boldsymbol{x}_{\text{bsf}}$ for all operational demands encountered.
2. Methods to query $\boldsymbol{x}_{\text{bsf}}$ for a given operation demand.

A great deal of processing of the time series are needed to ensure that the assumptions regarding the system setup are met before updating the knowledge database. It consists of, among other things, finding subsets of the time series where the system is in a stationary state. Important machinery measurements must be repeatable and independent of time. We make use of interval binning [12] of $\boldsymbol{y_d}$ to reduce the number of possible operational demands into a finite number. This makes it possible to store both the normalized costs and the decision variables in finite-dimensional data structures. Let us define some sets that facilitate concise descriptions of these data structures. The δ-discrete set is defined as

$$\mathcal{D}_\delta := \{x \in \mathbb{R} : \forall z \in \mathbb{Z}, \delta > 0, x = \delta z\}. \tag{4}$$

We define the δ-binned mapping $b(x;\delta) : \mathbb{R} \to \mathcal{D}_\delta$ as

$$b(x;\delta) := \min \operatorname*{arg\,min}_{z \in \mathcal{D}_\delta} |x - z|, \tag{5}$$

which takes a real number and assigns it to the appropriate bin interval (of width δ). Define the binning vector $\Delta := [\delta_1, \cdots, \delta_{n_y}]^\intercal$, where $\delta_i > 0$. We denote the multi-dimensional binning as $\mathcal{B}_\Delta : \mathbb{R}^{n_y} \to \mathcal{D}_{\delta_1} \times \cdots \times \mathcal{D}_{\delta_{n_y}}$ with definition

$$\mathcal{B}_\Delta(\boldsymbol{y_d}) := \left[b(\boldsymbol{y}_{\boldsymbol{d},i};\delta_i) \cdots b(\boldsymbol{y}_{\boldsymbol{d},n_y};\delta_{n_y})\right]^\intercal. \tag{6}$$

This mapping takes operational demand vectors and assigns them to appropriate bins, which are hyperrectangles. Suppose the range of relevant operational demands form closed and connected intervals of interest for each dimension. Denote this hyperrectangle as $\mathbb{Y} \subset \mathbb{R}^{n_y}$. The discretized set of operational demands for the region of interest is then

$$\mathcal{Y} := \{\boldsymbol{z} \in \mathbb{R}^{n_y} : \forall \boldsymbol{y_d} \in \mathbb{Y}, \boldsymbol{z} = \mathcal{B}_\Delta(\boldsymbol{y_d})\}. \tag{7}$$

The cardinality $|\mathcal{Y}|$ indicates the number of different bins for which we partition the space of operational demands. For each element of $\mathcal{Y}$ we need a mapping to the optimal decision $\boldsymbol{x}_{\text{bsf}}$. Since there are many candidate decision vectors that may give the optimal cost, we need to keep track of promising decision vectors and their corresponding normalized costs. Define the set of candidate solutions that belongs to a particular desired output $\boldsymbol{y_d}$ as

$$\mathcal{X}_D(\boldsymbol{y_d}) := \{\boldsymbol{x} \in \mathbb{X} : \mathcal{B}_\Delta(\boldsymbol{y_d}) = \mathcal{B}_\Delta(\boldsymbol{y}(\boldsymbol{x_c}, \boldsymbol{x_d}))\}. \tag{8}$$

For each element of $\mathcal{X}_D(\boldsymbol{y_d})$ there is a unique map to the normalized cost. The set of candidate costs are given by the set

$$\hat{\mathcal{C}}_D(\boldsymbol{y_d}) := \{z \in \mathbb{R} : \forall \boldsymbol{x} \in \mathcal{X}_D(\boldsymbol{y_d}), z = \hat{c}(\boldsymbol{x_c}, \boldsymbol{x_d}, \boldsymbol{y_d})\}. \tag{9}$$

The calculated optimal decision for a given $\boldsymbol{y_d}$ is approximated as

$$\boldsymbol{x}_{\text{bsf}}(\boldsymbol{y_d}) = \min \operatorname*{arg\,min}_{\boldsymbol{x} \in \mathcal{X}_D(\boldsymbol{y_d})} \hat{c}(\boldsymbol{x_c}, \boldsymbol{x_d}, \boldsymbol{y_d}). \tag{10}$$

This function returns the least element that has the smallest recorded normalized cost for that desired system output (also known as $c_{\text{opt}}(\boldsymbol{x}_{\text{c,opt}}, \boldsymbol{x}_{\text{d,opt}})$).

For each discretized operational demand (element of $\mathcal{Y}$) we need to hold two sets, namely $\mathcal{X}_D$ and the corresponding cost set $\hat{\mathcal{C}}_D$. The number of elements in these sets is limited to n_s. The procedure for updating the elements in $\mathcal{X}_D$ and $\hat{\mathcal{C}}_D$ is as follows. First, the correct bin is identified by inspecting the observed value of the system output $\boldsymbol{y}$. Then, the measured decision vector is compared against existing elements in $\mathcal{X}_D$. If a similar element exist*, the associated normalized cost is updated by a low-pass filter, for instance with exponential smoothing:

$$\hat{c}_{\text{new}} = (1-\alpha)\hat{c}_{\text{previous}} + \alpha\hat{c}_{\text{measured}}, \tag{11}$$

where $\alpha \in (0,1]$. Otherwise, if the observed value $\boldsymbol{x}$ is not one of the stored candidates, the handling of this measurements will depend on its normalized cost value. A new candidate solution replaces an existing candidate if only if $|\mathcal{X}_D| = n_s$ and the new cost is smaller than the old one.

Remark 1. *Interval binning of the operational decision space is a compromise. On the one hand, too small bins may lead to situations where a bin only has a sparse set of data as a basis for the decision making. The choice of $\boldsymbol{x}_{bsf}$ may then taken based on only a handful of observation (or worse: none). On the other hand, larger bins will ensure a better basis for decision making. The downside is that for large bins, the optimal decision may vary within the bin.*

CASE STUDY

The particular problem forming the background for this paper is choosing operational decisions for ships with many propulsion modes, such as various diesel electric and diesel mechanic configurations. This was part of the project PurSense [10], where four fishing vessels of comparable specifications were instrumented for gathering operational data and for presenting recommendations to the crew.

Vessel Integration and Data Collection

There are large variations with respect to how the vessels are equipped. As a generic framework has been the goal of this work, the integration has had to support different physical layouts as well as differences in protocols and available sensors. To reduce the amount of redundant work, the architecture focus on keeping such differences at as low a level as possible. This provides a common vessel interface for subsequent tools development. The actual interface is using a framework named *Ratatosk* developed by SINTEF Fisheries and Aquaculture, which is again based on the *Data Distribution System* (DDS) [13, 14] framework. The acquired data is cached on board the vessels while at sea and then sent to the SINTEF Marine Data Centre when the vessel is within range of mobile broadband connections.

Adaptation of method to case study

The general method was adapted to the specifics of the four vessels taking part in the case study. Specifically, the following definitions were used:

$$\boldsymbol{x_c} = \begin{bmatrix} M_{RPM} \\ P_{RPM} \\ P_P \\ PTI - PTO \end{bmatrix}, \tag{12a}$$

$$\boldsymbol{x_d} = \begin{bmatrix} PTI > 0 \\ PTO > 0 \\ \left|\frac{P_{RPM}}{M_{RPM}} - G_r\right| < a \end{bmatrix}, \tag{12b}$$

$$\boldsymbol{y} = \begin{bmatrix} u \\ T \\ e \end{bmatrix}, \tag{12c}$$

$$\tilde{f}_c = k_1 u^2 + e, \tag{12d}$$

where M_{RPM} is main engine speed, P_{RPM} is propeller speed, P_P is propeller pitch, PTI is power to electric propulsion, PTO is shaft generator power, G_r is gear ratio, a is a small allowance, u is vessel speed, T is vessel thrust and e is electric power consumption. G_r is chosen according to the recorded gear ratio when propeller and main engine is connected through the main gear. a is chosen according to the variations seen in the measurements to as accurately as possible define when the connection is active. k_1 is chosen to approximate the measured cost. The cost function c in the case study is the sum of the fuel consumption of the main engine and the auxiliary engines.

Offline Analysis

The purpose of offline analysis is to gain insights in how the different propulsion modes affect fuel consumption. This analysis combine data from all vessels subject to various operation conditions and vessel demands. Three sequential steps comprise the analysis. The first step corrects all measurements according to post-acquisition knowledge of scaling, variable renames, and sensor errors. The second step extracts representative combinations of values, taking into account events such as outliers and instability. The third step consists of various analyses to both assure the quality of the measurements and to gain insight in the vessel operations. Some results from these analyses are visualized in the Figs. 1 to 5, which are explained below.

The Operational Profiles of the Vessels The analysis is based on mapping thrust to normalized thrust. Normalized thrust is defined as an approximation to the ratio between actual thrust and the thrust expected for the same speed during ‘good’ conditions (e.g. no waves, empty vessel and no fishing gear). This mapping makes us able to compare measurements that are taken at different times but with similar additional ship resistance. The normalization function used in the present work is in the form:

*Two elements $\boldsymbol{x}$ and $\boldsymbol{z}$ are considered similar if $\boldsymbol{x_d} \equiv \boldsymbol{z_d}$, and $\boldsymbol{x_c} \approx \boldsymbol{z_c}$, e.g. using interval binning.

$$\hat{T} = \frac{T}{k_2 + k_3 u + k_4 u^2}, \tag{13}$$

where $\hat{T}$ is normalized thrust and k_2, k_3 and k_4 are constants chosen to make the normalized thrust speed independent, and to make a value of 1.0 representative of 'good' conditions. Figure 1 shows the distribution of vessel speed and normalized thrust averaged for the vessels that are part of this study. The colors in this figure denotes the frequency of every combination of vessel speed and normalized thrust. The figure indicates that the normalized thrust is speed-independent, and that the value 1.0 forms a rough lower limit. This is a sign that the resulting normalized thrust is a good approximation of the ratio between actual thrust and that expected for beneficial conditions. If interpreted with the context of understanding ship operational patterns, we can observe that common ship speeds are between 9 and 14 knots with thrust ranging from approximately 80 % to 160 % of what we expect under 'good' conditions (normalized thrust is between 0.8 to 1.6). We can also observe an area centered at 4 knots and normalized thrust 9. This region indicates pelagic trawling. An interesting observation of the thrust-speed plot is the quadratically decaying front for increasing speeds (the limit against the white area in the upper right half of the plot). For white regions there are no measurements available. The front probably indicates the maximum thrust the vessel is able to produce for each speed.

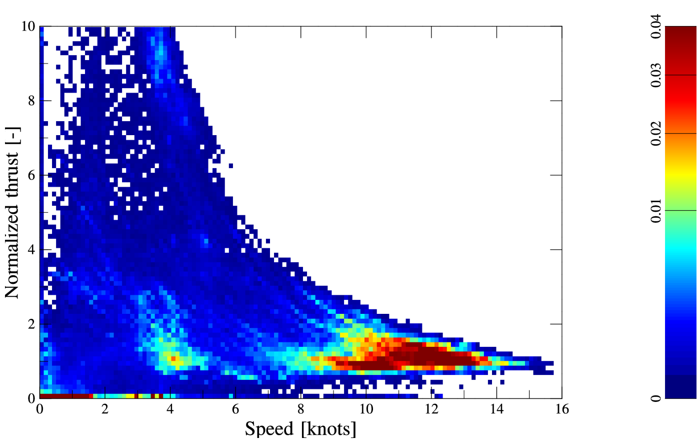

FIGURE 1. FREQUENCY DISTRIBUTION OF VESSEL SPEED AND NORMALIZED THRUST.

The Effect of Operational Decisions on Vessel Fuel Consumption. Figures 2 to 5 show the average normalized fuel consumption for variations in vessel demands and the operational mode selected by the crew. The normalized fuel consumption is an abstraction of the fuel consumption meant to emphasize the differences between choices, while reducing the variations in fuel consumption for different samples within the same histogram bin. Each curve represents a specific mode of operation for the energy system. Specifically, this is defined by the conditions: Are the propeller and the main engine directly coupled? Is electric power used for propulsion? Is the main engine used for generating electric power? The subset of modes indicated in these figures are as follows:

DE auxiliary engines: The propulsion is powered by the auxiliary engines through an electric motor.

DE main engine : The propulsion is powered by the main engine through an electric motor.

Split: The propulsion is powered by the main engine, and the shaft generator of the main engine is not active. The electrical system is powered by the auxiliary engines.

Shaft generator: The propulsion is powered by the main engine, and the shaft generator of the main engine is active. The auxiliary engines are shut down.

To limit the number of figures, only figures covering the most common operational conditions are shown in this paper. These figures are by no means representative for the ships operation and optimum decisions as a whole, but they give useful information about how the choice of operational mode affects fuel consumption.

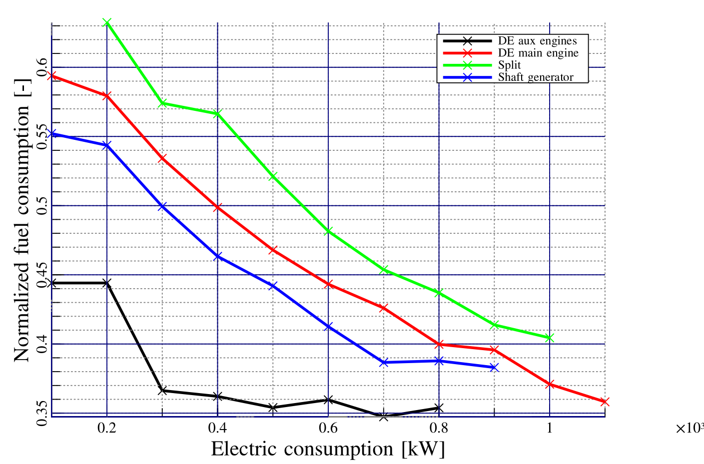

FIGURE 2. NORMALIZED FUEL CONSUMPTION FOR SPEED 10 KNOTS AND NORMALIZED THRUST 1.0.

Figure 2 shows how the normalized fuel consumption depends on operational mode for varying electrical consumption, given 10 knots speed and normalized thrust equal to 1. It is obvious that for these conditions, DE auxiliary engines is the best mode for electric consumption less than 800 kW. Lack of values for larger electric consumptions for the various modes is due to the fact that the vessels have not operated sufficiently long at these combination of conditions and operational decisions. This could be due to energy system limitations or crew decisions, or there may not have been such operational demands.

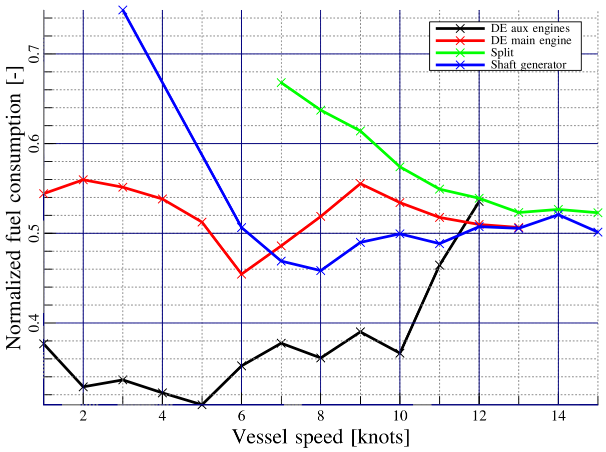

FIGURE 3. NORMALIZED FUEL CONSUMPTION FOR ELECTRIC POWER CONSUMPTION 300 KW AND NORMALIZED THRUST 1.0.

Figure 3 shows how the normalized fuel consumption depends on operational mode for varying vessel speed, given 300 kW electric power consumption and normalized thrust equal to 1. Again, it is obvious that DE auxiliary engines mode is beneficial in most of these situations where it is possible. The data also indicates that as the speed increases, the efficiency of this mode rapidly deteriorates in relation to other propulsion modes. This is to be expected, as the drawbacks of diesel mechanic propulsion (inability to reduce propeller speed below a limit) decreases with increasing speed and the drawback of diesel electric modes (efficiency of energy conversions) increases. It is, however, interesting that the same trend is not seen for DE main engine. This can be due to measurement errors, but it is also possible that the increasing efficiency of the main engine at increasing loads contributes to this effect.

Figure 4 shows how the normalized fuel consumption depends upon operational mode for varying normalized thrust, given a speed of 10 knots and an electric power consumption of 300 kW. It is seen that in this situation, DE auxiliary engines

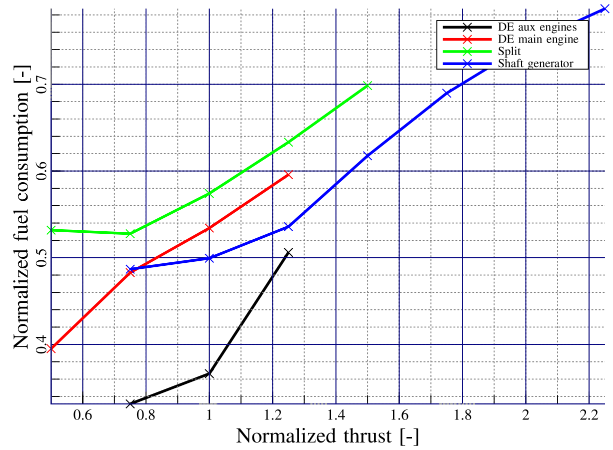

FIGURE 4. NORMALIZED FUEL CONSUMPTION FOR ELECTRIC POWER CONSUMPTION 300 KW AND SPEED 10 KNOTS.

performs best in the situations where it has been used. When the normalized thrust exceeds 1.25, Shaft generator is the most energy efficient choice.

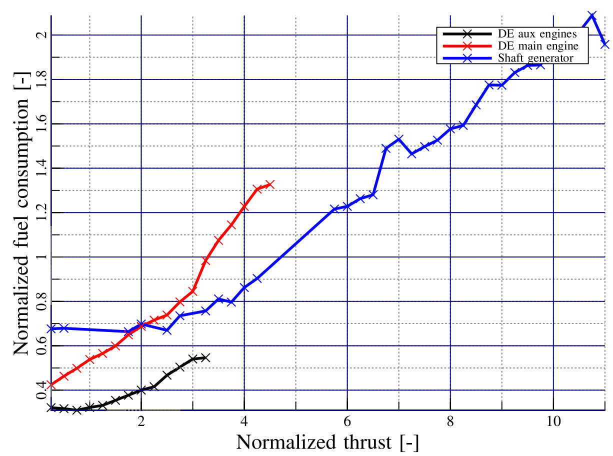

FIGURE 5. NORMALIZED FUEL CONSUMPTION FOR ELECTRIC POWER CONSUMPTION 300 KW AND SPEED 4 KNOTS.

Figure 5 shows how the normalized fuel consumption depends on operational mode for varying normalized thrust, given a speed of 4 knots and an electric power consumption of 300 kW. It is seen that in this situation, DE auxiliary engines performs best in the situations where it has been used. When the normalized thrust exceeds 3.5, Shaft generator is the best performing choice. This low speed is interesting since it is a typical trawling speed, which gives us data for high thrust levels.

Real-Time Advise on Current Operation

The aforementioned data structures keep an overview of how previous operational choices have affected the fuel consumption of the vessel for various combinations of operational demands. This makes it possible to not only find in real time if similar operational demands have been met more efficiently in the past, but also to inform the crew of the most beneficial choices made for this situation. This is implemented as a real time decision support system onboard the vessels. This tool contains various screens for informing the crew of the vessel efficiency, improvement potential and the historically best choices. A screenshot of one screen of this tool is shown in Fig. 6. Other screens inform the crew of e.g. how the vessel was operated when the best efficiency was achieved.

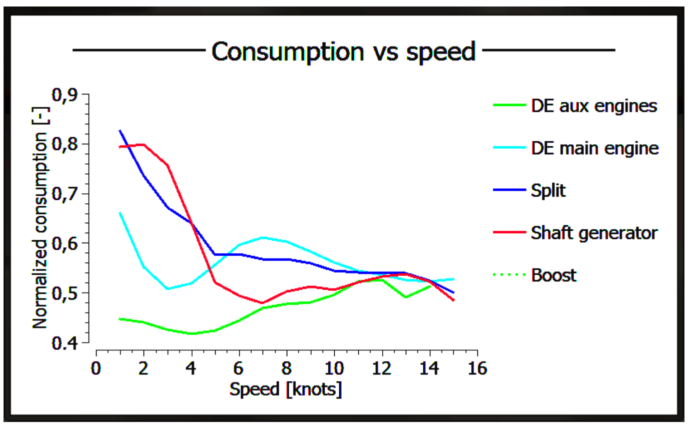

FIGURE 6. REAL-TIME DECISION SUPPORT TOOL SHOWING EXPECTED NORMALIZED FUEL CONSUMPTION AS A FUNCTION OF SPEED, FOR PRESENT ELECTRIC POWER CONSUMPTION AND SPEED.

CONCLUSIONS

Results

A generic framework for decision support based on finding the historical best solutions are presented. The framework is used in a case study on four similar vessels. This case study includes both offline onshore analyses and a tool for real-time decision support on board the vessels. The results seem promising, and have already given improved insight in how the efficiency of these vessels depend on the operational decisions. Still, there are some limitations to both the method and the results of the case study.

Method limitations

A decision support tool based on this method cannot evaluate (and thereby suggest) combinations of demands and choices which have not been previously measured. In addition, if only few of the best choices are stored, sporadic overly positive estimates for operational decisions not currently one of the n_s stored solution candidates may cause the history for more beneficial operational points to be lost.

Case study limitations

Accurate measurements of fuel consumption is both difficult and expensive to obtain, since marine diesel engines include a return flow of fuel. Especially for small power levels, one needs to measure both a large fuel flow *to* the engine and a slightly smaller fuel flow *from* the engine. Any inaccuracy in any of the measurements will therefore be very much amplified in the estimate of the fuel consumption. To improve the accuracy, the flow measurements for the main engines are replaced by an estimate based on the fuel rack position and the engine speeds. This seems to improve the results, but there is still a possible bias caused by the lack of calibration between the fuel consumption estimates of the main engines and the auxiliary engines. Such a bias would cause a strong bias towards some operational modes and reduce the benefits of this system significantly.

Another possible source of errors is the fact that propeller efficiency is assumed constant for a given combination of vessel speed, propeller speed and propeller pitch. Variations in propeller efficiency caused by effects such as ventilation, cavitation and ship movements are not considered.

FURTHER WORK

It will be important to calibrate the fuel consumption estimates of the main and auxiliary engines, to mediate the possible problems described above. Periods where either main or auxiliary engines are stopped will be identified, and consumption estimates will be compared to fuel tank measurements. If such periods can be found, this is expected to reduce any bias between use of main engine vs. auxiliary engines.

To address the method's inability to recommend solutions for which sufficiently data doesn't exist, the method could be preseeded with calculated estimates. If the benefits would outweigh the disadvantages are, however, not clear.

ACKNOWLEDGMENT

This work is carried out on behalf of the shipowners Ervik&Sævik, Eros, Kings Bay and Herøyhav. It is funded by the Research Council of Norway (grant no. 226378) and The Norwegian Seafood Research Fund (grant no. 900886).

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