# Data-Driven Methodology for the Analysis of Operational Profile and the Quantification of Electrical Power Variability on Marine Vessels

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***Abstract*—Measurements from the on-board systems of marine vessels are increasingly available for data analysis and are growing in importance as the ship industry enters a phase of digitalization. The purposes of the data analysis from vessels in operation include the verification of the power system design in general and improvement of the electrical power load analysis (EPLA) in particular. In this paper, we show how to extract valuable information from the data-driven operational profile analysis, which reveals the real power demand, and how the vessel was operated. Using the real power range analysis, we emphasize the significance of rarely occurring high power demands, which are critical for power system design and optimization. We propose a methodology for the quantification of variability in the generated power, which explains the tails of probability distributions of a power signal based on signal decomposition. The proposed methodology makes use of the data and it can facilitate the selection of the optimal size, number, and configuration of generators or batteries when designing new power systems. Measurements from a data collection system are used to demonstrate the methodology for dynamic positioning (DP) mode of the operation of a platform supply vessel (PSV).**

***Index Terms*—electric power load analysis (EPLA), power variability quantification, load variability, power system design.**

## I. Introduction

**P**OWER systems have a significant role in marine vessels to propel the vessel and to cover the demand for various loads during operations of the vessel. Power plants of modern vessels are growing in size and complexity with increasing demand for ship size, speed, safety, operability, and economy [1]. The interconnections between the power system and diverse systems on a vessel have become increasingly complex, making the design, engineering, and building of a vessel a more integrated effort [2]. The main power system design tasks include: selection of the optimal power system configuration, load analysis (which supports the selection of the right number and size of electrical power generators), and selection of the configuration and the size of power distribution for propulsion and service loads. The power system design is made based on the personal experience and knowledge gathered from prior vessel designs. Additionally, there are many rules and regulations imposed by the International Maritime Organization (IMO), National Authorities and classification societies, e.g., Det Norske Veritas-Germanischer Lloyd (DNV-GL), American Bureau of Shipping (ABS), or Lloyd's Register (LR), which establish the requirements for the power system design and redundancy. Recommended standards for designing the shipboard power systems include, e.g., [3], [4]. For many vessels there will also be additional class notations and recommended practices, depending on the function of the vessel, e.g., DP class [5], [6]. Improvements in the power system design can be supported by mathematical modeling and simulations (based on physical and empirical laws) [7]–[9] or data-driven modeling (machine learning, statistical approach) [10]–[12].

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This work was supported by Rolls-Royce and funded by The Research Council of Norway under Project 251823.

### A. Challenges in power system design

The electrical load lists, containing load factors, are standard procedures for the dimensioning of vessel power systems. The power demand is determined by assigning a load factor to each electrical consumer, based on the experience from similar ships [1], [13]. This method has limitations, since the output is only a single number and the range of possible combinations of loads remains unknown. Simultaneously, the current load factors do not reflect the way in which the equipment is operated [14]. Traditional methods based on the load factor are often not found sufficient in cases where vessels have large varying electrical loads, because many load deviations appear during a specific operation [13].

Therefore, a stochastic load analysis will be more appropriate for the power system design and this method is described in a design data sheet (DDS) [15]–[17]. The important impact of performing stochastic load analysis is the determination of the minimum, mean, and maximum loads, what is a challenge. Making correct assumptions regarding a range of expected loads enables more appropriate sizing of generators. Therefore, the assumptions about operational profile and the real power load range used in various operational modes are crucial.

Challenges in power system design, such as expected load ranges, total load demand, and power variability in real conditions [18], [19] have prompted researchers to focus on the efficiency of power systems and few alternative techniques to perform EPLA were proposed [20]–[22]. To improve power system efficiency, power system optimization has become crucial to reduce operational and installation costs. Optimization methods were applied using a classifier-guided sampling [23] or heuristic solution Generic Algorithm [22] based on power demand calculated using load factors or the stochastic approach with Monte Carlo simulation. An important approach for power system dimensioning is load modeling using behavioral models of loads for smaller power systems [17]. All these methods shows that there is scope for power system optimization and adjustment of a designed peak power; this motivates to analyze real power requirements of a vessel applying measurements.

### B. Support of power system design by data analysis

As we described above, the major challenge in the power system design is assumptions about load ranges. The loading on thrusters will vary greatly depending on the weather conditions; however, the proper number and the size of generators will be optimized for the worst case heavy sea and maximum power, which is not the most probable scenario [13]. Therefore, sometimes we can see non-efficient installations.

Marine diesel engines of offshore vessels in a DP mode are typically operated at 20–50% of maximum continues rating (MCR); however, their optimum is about 80% MCR (see Fig. 1), which causes non-efficient and expensive operations with high fuel consumption. The aim of power system design is a choice of an engine with an operating point at 80% MCR. To overcome that challenge, we can use real measurements from the monitoring systems of vessels and apply the data-driven methodology to improve standard design methods and verify the current power systems. By a careful study of real power demands and rarely occurring high power and variability, we are able to adjust the size of the engine to fit the most economic and environment-friendly operational point of the engine.

The knowledge about real power demand lets us to choose the optimal size of generators by adjusting the peak power limits (see Fig. 2). Then we can install additional power source to cover loads above the set limit or to cover the power variability by adding new equipments like batteries or capacitors. This will let the engines run at more optimal and constant load and enhance the vessel safety for optimized installation.

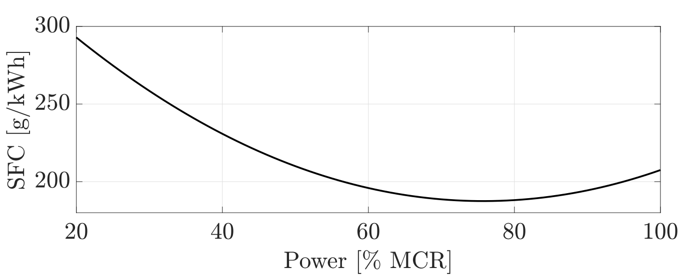


Fig. 1: Specific fuel consumption (SFC) for a medium speed diesel engine [24]

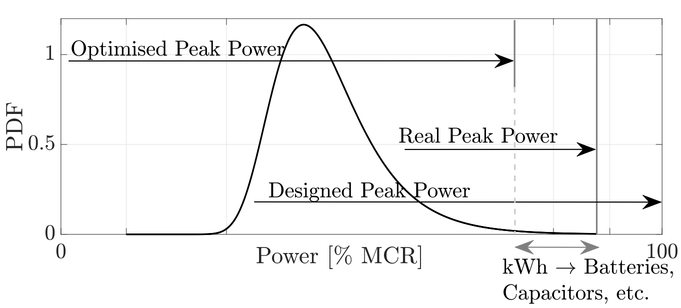


Fig. 2: A typical probability distribution function of power generated. MCR refers to generator rated power at $\cos\phi = 0.9$

Thus far, measurements from on-board systems of a vessel have been used to estimate load of economic operation of electric generators and load shedding and were applied involving pattern recognition techniques [25]. Measurements were used to establish the representative load curves based on 15-min average power demand over a time horizon [26] and to cluster load profiles for electric consumers of a ship [27]. The research on load curve classification was originally conducted for short-term load forecasting of anomalous days [28] and to cluster power systems customers [29], [30].

This implies that the analysis of measurements can be applied to improve power system design [26] and to increase the knowledge on complex power systems.

Additionally, data analysis allows:

- support for dimensioning of the batteries. In the past several years, focus on the environment has increased and led to the application of energy storage and use of renewable energy sources in marine power systems. The advantages and disadvantages of installing batteries for application in peak shaving and load shedding are reported in [31]–[35];
- onboard optimization of the configuration, e.g., turning on or off generator sets or connecting additional switchboards depending on the load level, or cyclic operation with batteries (charge/discharge);
- optimization of the onboard operation of the power system that includes control strategies, and coordinated control based on the level of power variability [1], [36].

As we see, there is room for power system design optimization; however, we have to study, understand, and investigate the power variability and rarely occurring power demands to avoid underestimation and to ensure vessel safety.

### C. Overview of the paper

In this paper, we propose the use of the vessel operational profile analysis for power system design verification, based on real measurements from an on-board monitoring system. Operational profile analysis enables establishing real load ranges and motivates to study high and rarely occurring power demands.

We propose a methodology for the quantification of variability and dynamics originating from different types of operational loads and weather conditions affecting the generated power based on the one-year data from a PSV in a DP mode. The outputs of the method, namely probability distributions of a power signal, enhance the knowledge of the portion of the load originating from varying electrical consumers and environmental factors. We emphasize the need to study rarely occurring high power demands, which appear in tails of probability distributions of a power signal, and it can be explained with the quantification of variability in power. The methodology can help to facilitate the selection of the optimal size, number, and configuration of generators or batteries when designing new power systems as well as can be applied to analyze various types of power systems of vessels.

In the section II of this article, we present the typical power system set-up of the vessel, from which we analyze the data. Then, in section III, we describe the analysis of operational profile of the vessel based on probability distributions. In section IV we describe and motivate the methodology for power decomposition. In section V and VI we describe the application case and practical applications of the proposed methodology. Finally, we present the main conclusions.

## II. Power system set-up of the vessel

As an example, to illustrate the methodology of analysis, we use a PSV with a diesel-electric configuration and a power system set-up shown in Fig. 3. The total generated electrical power is the total power output of four generators (G), $y[n] = \sum_{i=1}^{4} y_i[n]$ ($n$ is number of measurements, $y_i[n]$ is power generated by the $i$-th generator), connected to the main 690 V switchboard and equivalent to 100% (values are anonymized). The signal of the total generated power is registered by an on-board monitoring system and sampled with the sampling frequency of 1 Hz. Power generated by the generator is a 4-20 mA signal from a multi-transducer in the main switchboard, based on inputs from the three current transformer and three-phase voltage.

The main power consumed is the sum of power used by the two main propulsors (M) and the three thrusters (T), $x[n] = \sum_{i=1}^{5} x_i[n]$ ($x_i[n]$ is the power consumed by the $i$-th main consumer). Power consumed is limited only to the main power consumed by large consumers. The difference, $y[n] - x[n]$ is represented by hotel loads and part of the operational loads, which are not measured directly.

## III. Operational profile analysis

Operational profile analysis is a known method to understand how a vessel has been operated over a period of time. An operational profile shows the percentage of time in which a vessel has been in a specific mode of operation, i.e., the amount of time in which a vessel was in a DP, transit, or any other specified mode.

The first steps of the operational profile analysis are to establish the definitions of different vessel operational modes

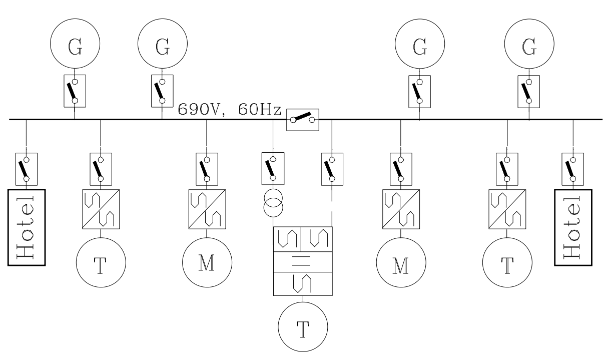


Fig. 3: A typical power system set-up of the vessel.

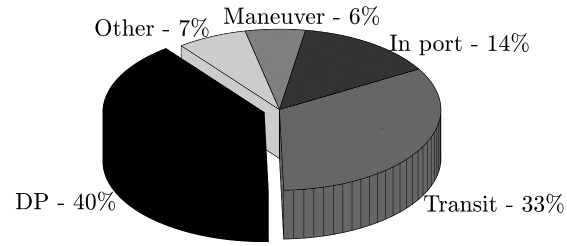


Fig. 4: The operational profile of a PSV in one-month of operation

[1] and to apply them to available measurements, in order to quantify the time spent in each of the mode of operation over a specific period. In Fig. 4, we show the one-month operational profile for a PSV operating in the North Sea. PSVs need to have good maneuverability and station-keeping capabilities in order to keep a vessel in position during operations at the platform. Using operational profile analysis allows us to assess which modes of operation occur most frequently. Fig. 4 shows that the vessel was mostly performing the DP (station-keeping) operations, which is a major operational task for this type of vessel; therefore, we focused on this vessel operation. The advantage of having measurements and the operational profile is the possibility to study the distribution of the total generated power in each of the operational modes, as described in the next subsection.

### A. PDF and CDF for specific vessel operations

Statistical properties of the analyzed electrical power distributions and maximal load ranges of power can be assessed by using the following functions [37]: cumulative distribution function (CDF) and probability density function (PDF).

As an example, in Fig. 5, we present a PDF and CDF of the total power generated and consumed in a DP mode for one-year measurements. These plots enable us to see the most probable and maximal electrical loads. We can assess that in a DP mode, approximately 99% of the time, the total electrical power, both generated and consumed, is below 40% of the total power available. This is connected with redundancy requirement. In addition, the maximum power produced is 69% of MCR; this gives us an indication of design margin as a difference between the designed and real peak power in this mode of operation.

The probability distribution of total power generated and consumed, in specific modes of operation, can be used for the verification of size and margins of the power plant and as an input for the power system optimization which should be preformed for each mode of operation. Additionally, the PDF tails and even 1% of high loads can be important in case of special purpose vessels, so it is required to carry out an in-depth study of high loads, the frequency of their occurrence, and the PDF tails.

For different type of vessels, a PDF and CDF analysis can be used to identify the critical vessel operations from the power perspective, i.e., to verify in which mode the vessel used the maximum power, the percentage time duration for which the vessel was in this operation mode and the critical

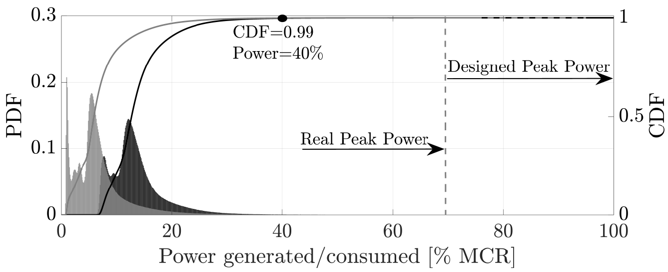


Fig. 5: PDF (left axis): electrical power generated (black), power consumed in a DP mode (gray), CDF for the relevant PDFs (right axis). % MCR refers to the generator-rated power, values are anonymized.

operation when the maximum power was used. For example, for fishing vessels, it will be trawling, and for ferry, it will be maneuvering.

In the next section, we will describe a method for the power decomposition, which is able to explain the variability in power measurements linked with the PDF tail.

## IV. Electrical power analysis based on power signal decomposition

The probability distributions of a electrical power signal depend on the mode of operation of the vessel. Additional information can be obtained by performing a time series analysis of the generated power. The total generated power signal contains a large amount of dynamics and/or variability. Large variability in the power system can be caused by operating the vessel in harsh environmental conditions with varying operational loads, and it can explain the PDF tail.

In Fig. 6, we see the example of classification variability of power signal in the function of frequency. We can see that loads are associated with frequency bands, e.g., steady-state loads from operations of the vessel are present at low frequencies and they vary slowly; varying loads from operations associated with environment appear in the frequency band $[f_1, f_3]$, which is motivated by the ocean wave classification [39] and ocean wave spectra [40], [41]. The most-influenced loads by environmental conditions are propulsion loads which are used to keep the position of the vessel in a DP operation.

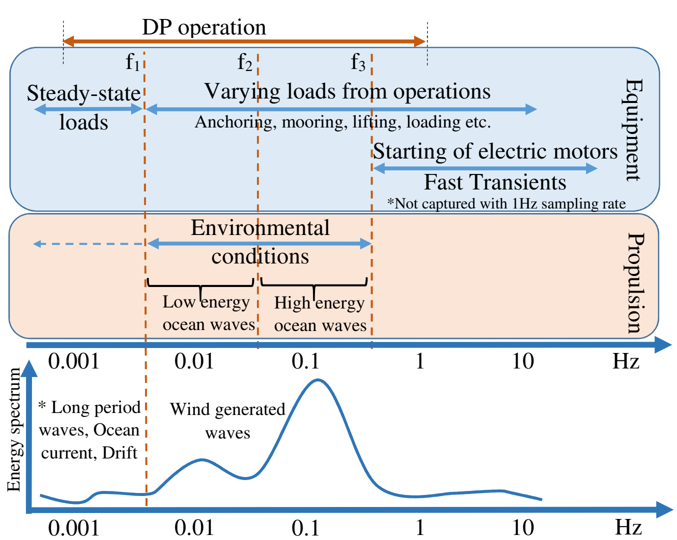


Fig. 6: Typical variability in power signal [24], [36], [38], [39]

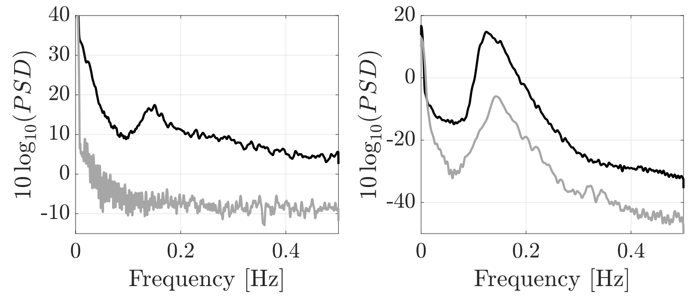


Fig. 7: Influence of the weather conditions on the power generated by generators. Left subplot: spectrum of the power generated for large vessel's motions (black) and power generated for small vessel's motions (gray). Right subplot: spectrum of the vessel's pitch for large pitch motions (black) and small pitch motions (gray).

Based on the ocean spectrum we can see that the long period waves have smaller energy spectrum than the shorter waves. The measured frequency spectrum for a heavy sea shows the high peak for the frequency band $[f_2, f_3]$ [42]–[44]. Similar peaks we see in the spectrum of the vessel's motion signals (vessel's roll and pitch) are associated with the sea conditions (see Fig. 7). From Fig. 7, we see that the peak in the frequency band related with the environment also appears in the spectrum of the power generated signal. Based on the Fig. 7, we can conclude that the environmental conditions effects the power generated. The most impact of the environment is in the frequency band $[f_2, f_3]$; however, based on the ocean wave spectra, we know that some influence of the long waves will be in the frequency band $[f_1, f_2]$. To conclude which frequency band and which loads are associated with the power probability distribution tail, we are motivated to use three filters to extract these frequency bands and see how they affect the power probability distribution in the further analysis. More details about the choice of frequencies are given in section V, based on the application example.

### A. Overview on the proposed methodology

In order to analyze the electrical power generated by the generators, we propose a methodology for power signal decomposition, which is presented in Fig. 8 in a block diagram. The key aspect of the methodology is to separate the power signals into appropriate frequency bands in order to extract information related to the phenomena at slow, medium, and high frequencies. In order to study and quantify the range of variability of the power generated in the time domain, digital filtering is used to decompose the signal. The first step of the methodology is the spectral analysis of the power signal, which is used, in combination with additional signals such as vessel pitch and roll, to link frequency properties of the analyzed signal to the vessel's operations and environmental conditions. In the frequency domain, we can select the frequency bands

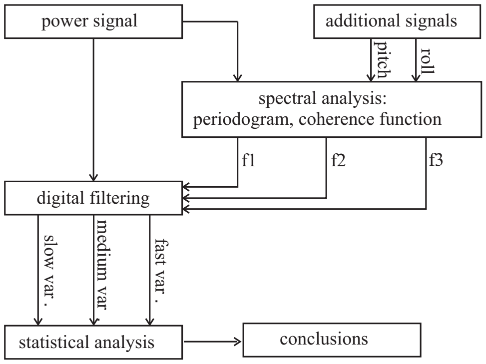


Fig. 8: Block diagram of the methodology for the quantification of dynamics in the generated power.

that are linked to the rate of change of the power signal. The choice of cut-off frequencies is made through the inference in the frequency domain on the significance of frequency bands:

a. Low-pass ($LP$) filter (cut-off frequency $f_1$), which extracts the low frequency component, is associated with slowly changing, steady-state operational loads
b. Band-pass ($BP_1$) filter (cut-off frequency $f \in [f_1, f_2]$), which extracts the medium frequency component, is associated with operational loads and low impact of weather conditions
c. Band-pass ($BP_2$) filter (cut-off frequency $f \in [f_2, f_3]$), which extracts the high variable component, is associated with the high impact of environmental conditions.

Applying digital filtering enables us to extract desirable frequency bands from the power signals. In the next stage, we apply descriptive statistics to signals obtained at the output of digital filters. In the final step, the quantified variability from frequency bands is linked to the total power of the system. By the association of frequency bands with the power variability, we can explain which loads influenced the high power demands and PDF tails. The estimated value can be used in the vessel's electrical power load analysis and power system optimization for new vessels.

The main objective of the described methodology is to show relevant steps that should be performed on a large data set to extract information on power variability. A large data set represent at least one year of measurements (continuously registered) that contain sufficient representations of possible scenarios; therefore, the data is assumed to be representative. All measurements are split according to operational modes. Each vessel operation should be analyzed separately because of various probability distributions functions of power (in our case, we analyze the DP mode). Spectral analysis based on periodogram and coherence function should be applied by averaging periodogram and coherence function after the set of realizations. This approach allows minimization of the influence of noise on the final results. However, for insufficient data set, this analysis may lead to poor results. To provide robust results that can be used for power system design, the analysis should be repeated on measurements obtained from few vessels that are of similar type and have similar operational area. In addition, the outcome of the analysis can be reinforced by simulations. An extension of the proposed methodology, on the basis of analysis of power variability from several vessels, may result in generalizations of probability distribution functions of power signal by fitting one of the common distribution; however, this is presently out of scope of the paper.

The proposed methodology applies to new vessels that have similar operational profile and area as well as for retrofits of old vessels where owners would like to install, e.g., batteries and implement more environmental friendly and efficient operations. The proposed method allows a more accurate design of installations of new (similar) vessels, validation of the power installation of existing vessels, and possible development of new concepts on the basis of knowledge gained from measurements and analyzes. It allows to validate assumptions of peak power and adjust the size of engines or propose batteries and dimension it.

In the following subsections, we will describe the applied techniques and show the practical example of application.

## B. Spectral analysis

Frequency domain analysis is well known in the field of electrical engineering. In the case of random signals, the standard method for spectral analysis is power spectral density (PSD, periodogram) [45]. Actual measurements include random elements, which suggests the use of the PSD for the frequency domain analysis. In this case, we assume that the signal is stationary in a wide sense [37], i.e., the mean value of the signal do not depend on time and the average value of the product of two samples depends only upon the time interval between samples. The PSD quantifies the distribution of power with frequency and it is defined in the following way [46]:

$$P_x(f) = \lim_{M\to\infty} \frac{1}{2M+1} E\left[\left|\sum_{n=-M}^{n=M} x[n]e^{-j2\pi fn}\right|^2\right] \quad (1)$$

where $E$ is the mean value, $M$ is the number of samples, $f$ denotes discrete-time frequency, which is assumed to be in the range $-0.5 \leq f < 0.5$. There are a number of methods for the PSD estimation [47], [48]. In practice, the most common is the Welch method [48], which ensures the bias-variance tradeoff. Periodogram, defined by (1), can be applied as a detector of a sinusoidal signal embedded in random noise [46], [49], [50] and is called generalized likelihood ratio test (GLRT). That detector has optimal properties, termed uniformly most powerful invariant or within a restricted class of detectors it has the highest probability of detection [51]. Therefore, conclusions about the presence of a signal in the selected frequency band can be drown on the grounds of periodogram properties.

A signal analysis based on a periodogram shows significant frequencies and their importance. Therefore, it is a common step in the quantification of signal variability. In order to delve the information from a periodogram, we propose to use a coherence function. A coherence function can provide additional information on the relationships between signals and can be defined as [46]:

$$|\gamma_{x,y}(f)|^2 = \frac{|P_{x,y}(f)|^2}{P_x(f)P_y(f)}, \qquad |\gamma_{x,y}(f)|^2 \leq 1 \tag{2}$$

It is sometimes called the coherence-squared function [52], where $P_{x,y}(f)$ is cross-power spectral density (CPSD) of two joined (stationary) random processes as [37]:

$$\begin{aligned} P_{x,y}(f) = & \lim_{M\to\infty} \frac{1}{2M+1} \cdot \\ \cdot E & \left[ \left( \sum_{n=-M}^{n=M} x[n] e^{-j2\pi f n} \right)^* \left( \sum_{n=-M}^{n=M} y[n] e^{-j2\pi f n} \right) \right] \end{aligned} \tag{3}$$

The coherence function has the following properties [46]:

- if $|\gamma_{x,y}(f)|^2 = 1$ then $x[n]$ and $y[n]$ are linearly related;
- if $|\gamma_{x,y}(f)|^2 = 0$ then the two signals are uncorrelated;
- if $0 < |\gamma_{x,y}(f)|^2 < 1$ then $x[n]$ and $y[n]$ are partially related. Possible deviations from the linear relationship between $x[n]$ and $y[n]$ include:
  - noise may be present in the measurements of either or both $x[n]$ and $y[n]$
  - $x[n]$ and $y[n]$ are not only linearly related

Based on the foregoing properties, we see that the coherence function can be interpreted as the squared correlation coefficient between the signals at given frequencies.

The tools described above allow us to interpret properties of the power signal in the frequency domain. Based on the spectral analysis, we choose desirable cut-off frequencies which are used for the specification of digital filtering. For spectral analysis we used nonparametric methods which assure unbiased estimation of the power density spectrum and additionally averaging after the set of realizations results in a reduction of the variance of the estimator, more details can be find in [47], [48]. The basics of digital filtering are described in the next subsection.

### C. Digital filtering

In order to perform a detailed statistical analysis of the power decomposed into different loads, we apply the LP and BP filters.

All filters are finite impulse response (FIR) filters designed based on windowed Fourier series [45]. All filters have the same length of the impulse response. Applied FIR filters guarantee a linear phase response and do not introduce phase distortions, which is crucial for the synchronization [53] and is necessary for proper analysis.

Based on the digital filtering, we decompose the generated power signal into three components and enable the statistical analysis of each component. The appropriate tools for a statistical analysis will be described in the next subsection.

### D. Statistical analysis

By using the theory of stochastic processes, it can be shown that signals at the output of the filters are uncorrelated [37]; this can be expressed as follows:

$$\begin{aligned} E(x[n]) = E(x_{LP}[n]) + E(x_{BP_1}[n]) + \\ + E(x_{BP_2}[n]) + E(x_{noise}[n]) \end{aligned} \tag{4}$$

where $x[n]$ is power generated, $x_{LP}[n]$ is the signal at the output of the LP filter, $x_{BP_1}[n]$ is the signal at the output of the $BP_1$ filter, $x_{BP_2}[n]$ is the signal at the output of the $BP_2$ filter, and $x_{noise}[n]$ is the signal component from frequency $f > f_3$ Hz. This can be interpreted as follows: the average value of the sum of signals (in this case signal $x[n]$, which we decompose) is equal to the sum of the average values from each signal. Additionally, the variance of signals is determined as follows:

$$\begin{aligned} var(x[n]) = var(x_{LP}[n]) + var(x_{BP_1}[n]) + \\ + var(x_{BP_2}[n]) + var(x_{noise}[n]) \end{aligned} \tag{5}$$

and PDF are associated by formula [37], [54]:

$$f_x(x) \cong f_{x_{LP}}(x) * f_{x_{BP_1}}(x) * f_{x_{BP_2}}(x) * f_{x_{noise}}(x) \tag{6}$$

where $*$ is a linear convolution defined by:

$$f_x(x) = f_y(x) * f_z(x) = \int_{-\infty}^{\infty} f_y(u) f_z(x-u) du \tag{7}$$

For the statistical analysis of power decomposed into three components $x_{LP}[n], x_{BP_1}[n]$ and $x_{BP_2}[n]$, we propose the use of a PDF. Looking at the plot of a PDF of a signal at the output of filters, we can see the distribution shape, the most common values, and the PDF tail.

In order to quantify the variability of each frequency component in the power signal, it is necessary to assess the dispersion of the distribution. To compare and establish the dispersion of each distribution, we propose to use variance and range, $R$:

$$R = x_{max} - x_{min} \tag{8}$$

where $x_{max}$ and $x_{min}$ are largest and smallest values of the distribution, respectively. Additionally, based on a definition of quantile $Q$ of order $p$ :

$$Q(p) = \{x_p : F(x_p) = p\} \tag{9}$$

where $F()$ is a distribution function, we propose to use the modified interquartile range [55], $IQR_m$, which is defined as follows:

$$IQR_m = Q(0.9985) - Q(0.0015) \tag{10}$$

It is worth noting that, based on formulas (9) and (10), $IQR_m$ describes the width/range of the interval $P[x_{0.0015} \leq X \leq x_{0.9985}] = 0.9985 - 0.0015 = 0.997$, i.e., this is an interval that contains $99.7\%$ of values of the random variable $X$.

The motivation for applying the modified interquartile range is the use of the $3\sigma$ rule of thumb for Gaussian distributions. Quartiles are less sensitive in case of outliers and distributions with long tails, which helps to achieve a robust estimation of the PDF dispersion and quantification of the load variability. This property is useful for the analysis of measurements distorted by noise.

It can be noticed, that properties of $R$ and $IQR_m$, have not additive properties, i.e.:

$$\begin{aligned} R(x[n]) \neq R(x_{LP}[n]) + R(x_{BP_1}[n]) + \\ + R(x_{BP_2}[n]) + R(x_{noise}[n]) \end{aligned} \tag{11}$$

$$\begin{aligned} IQR_m(x[n]) \neq IQR_m(x_{LP}[n]) + IQR_m(x_{BP_1}[n]) + \\ + IQR_m(x_{BP_2}[n]) + IQR_m(x_{noise}[n]) \end{aligned} \tag{12}$$

TABLE I: Power decomposition frequencies

| Loads | Frequency [Hz] |
|---|---|
| Slow variable Loads | $f_c < 0.005$ |
| Medium variable Loads | $f_c \in$ [0.005,0.05) |
| Fast variable Loads | $f_c \in$ [0.05,0.25] |
| Noise | $f_c > 0.25$ |

## V. Application case of the methodology

In the following section, we present the application of the proposed methodology as a case study for the generated power, vessel roll and pitch signals from a PSV with a diesel-electric configuration in a DP mode (see Fig. 3). The fragments of measurements were selected by analyzing one-year time series and by choosing extreme and representative examples which fulfil the stationarity in a wide sense condition [37] and have a high variance. In the design of power system such extreme cases are the most critical and the power system is dimensioned for the worst case weather scenario, therefore we concentrate on such cases.

An example of the waveform of the power signal is shown in Fig. 9. The slow variable component of the signal is shown in black. We can see a significant difference between the slow variable component and the instantaneous values. Looking at the time domain analysis, we can see that the power signal has high variability. This leads us to a study of signal properties in the frequency domain.

*1) Spectral analysis:* Based on the spectral analysis, we select frequencies that are linked to different electrical loads and are used for digital filtering and power decomposition. In Fig. 10, we show the normalized PSD of the total generated power (black) together with motions measurements of the vessel associated with weather conditions, vessel pitch (black dotted) and vessel roll (black dashed). The analysis of PSDs the from one-year data, verifies the choice of frequencies $\{f_1, f_2, f_3\}$ described in section IV. Additionally, the choice of frequency band $[f_2, f_3]$ is motivated by the dominating wave frequency [38]. Chosen frequencies are summarized in Table I.

Additionally, the selected frequencies presented in Table I can be verified by a coherence function of the generated power and the vessel's roll and pitch signals, which are shown in Fig. 11. Based on the coherence function, we can see that vessel motions, which are influenced by the environment, can explain approximately 50% of variability in the medium variable loads frequency interval $[f_1, f_2]$ and approximately 45% in the fast variable loads frequency interval $[f_2, f_3]$. The assessment of the influence of the environment based on the coherence function can be underestimated due to a high level of noise, especially in the case of the fast variable component. Therefore, in order to analyze the environmental impact, it is recommended to use simultaneous analysis of the normalized PSD and coherence function.

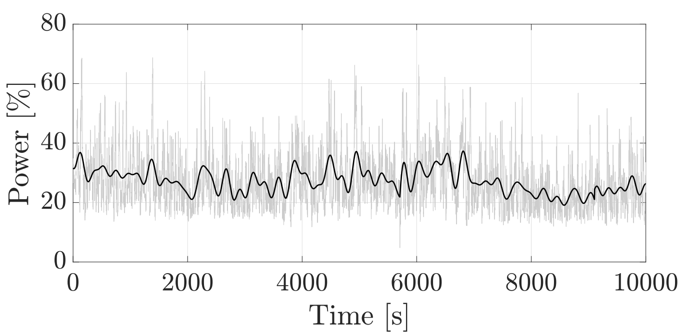


Fig. 9: An example of the waveform of the power signal (gray) and slow variable component (black) of the generated power.

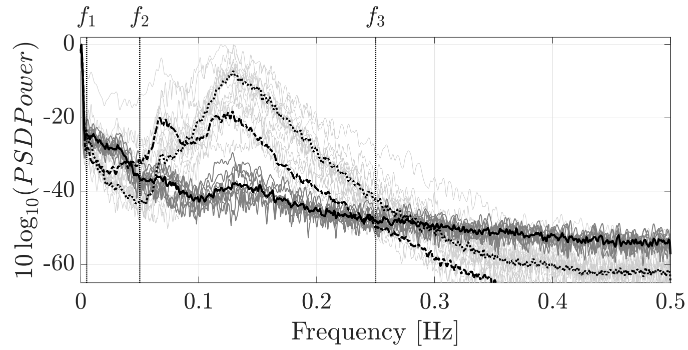


Fig. 10: Overlay plot of PSDs and ensemble average for the power generated signal (black), vessel pitch (black dotted), vessel roll (black dashed).

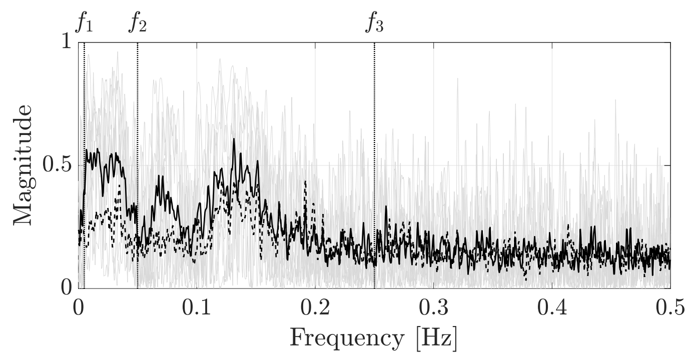


Fig. 11: Overlay plot of coherence functions and ensemble average for the generated power and vessel roll (black) and for the generated power and vessel pitch (black dashed).

Based on the spectral analysis (Fig. 10 and Fig. 11), we see that the generated power can be decomposed into load fluctuations, which are linked to different frequency bands. This analysis can be performed for the entire power system and for a single power consumer, such as the main propulsion thrusters or bow thrusters, in order to see the power dynamics/variability. This leads to the use of digital filtering as a tool for the extraction of load fluctuations from a specific frequency band, enabling the quantification of the dynamics originating from different loads in the power system.

For the power decomposition, we apply three digital filters, as described in section IV.C, with the cut-off frequencies defined in Table I.

*2) Statistical analysis based on electrical load distributions of decomposed power:* A statistical analysis allows for power dynamic quantification based on the dispersion of distribution from the decomposed power. Quantification of power dynamics plays a crucial role in the system optimization, where

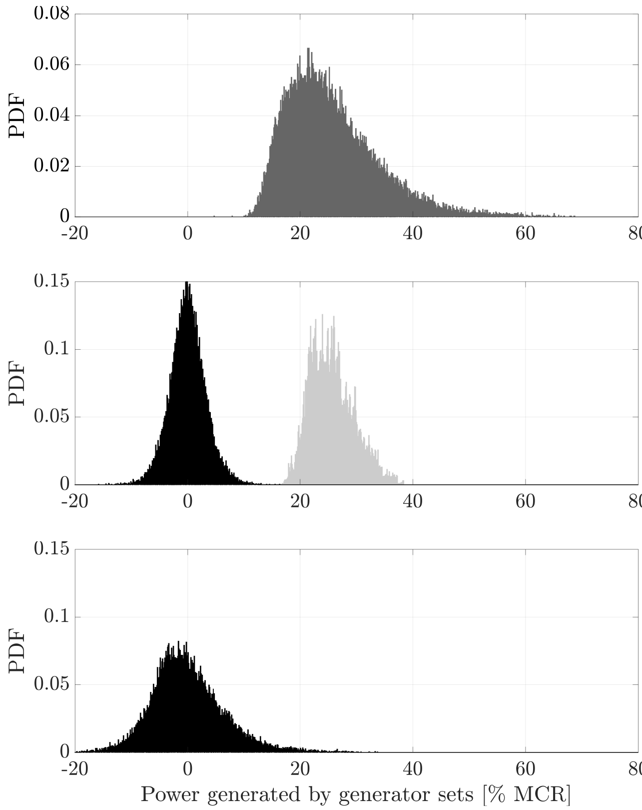


Fig. 12: Load distributions of the power decomposed into various frequencies. Upper subplot: PDF of the power generated (dark gray); Middle subplot: PDF for the power decomposed into: slow varying loads (light gray), fast varying loads (black); Lower subplot: PDF for the power decomposed into medium varying loads (black). % MCR refers to the generator-rated power at $\cos\phi = 0.9$; values are anonymized.

design margins are adjusted to maximal real loads. In the upper subplot of Fig. 12, we showed PDFs of the total electrical power generated by four generators. We see that the distribution is unimodal and the mean value is approximately 26% of the total power available. The distribution is skewed right. The maximal value is equal to 69 % of the total power available. We showed all distributions of the decomposed signal in the subplots of Fig. 12. Analyzing the output of the LP filter (light gray, the middle subplot), we see the lower range of distribution compared to the primary distribution. Therefore, the wide range/dispersion of the PDFs of the total generated power can be explained by the PDFs originating from the output of BP filters (black distributions, see formula (5)). The most significant difference between these distributions is the difference between their ranges/dispersion. Looking at this, we see that the tail of the probability distribution of a power signal can be explained by the range of the medium varying loads (black distribution, the lowest subplot), which further can be explained by the slowly changing operational loads and some influence of the environmental conditions. The fast varying loads, predominantly linked to the environmental factors, have the smallest dispersion.

TABLE II: Descriptive statistics for distribution (all values in [% MCR]).

| Loads | $x_{min}$ | $x_{max}$ | $R$ | $IQR_m$ | mean | var |
|---|---|---|---|---|---|---|
| Total | 4.8 | 68.8 | 64.0 | 49.5 | 25.6 | 68.5 |
| Slow | 12.6 | 38.3 | 25.7 | 20.6 | 25.6 | 15.3 |
| Medium | -22.1 | 33.7 | 55.8 | 44.4 | 0 | 40.6 |
| Fast | -15.6 | 16.3 | 32.1 | 21.5 | 0 | 10.0 |

Descriptive statistics of distributions are summarized in Table II, which confirms the results described above. Based on the results presented in Table II, we see that the difference between the range $R$ and $IQR_m$ is not significant for slow, higher for medium and most significant for fast variable loads. The significant difference observed in the case of fast variable loads is a result of noise level in the frequency band. Therefore, a more appropriate method for power the variability quantification, which is less sensitive to noise, is $IQR_m$.

Interpretation of statistical properties of signals after decomposition can be associated with analysis of time series and properties of Fourier transform (FT). Fig. 13 shows a close-up of time series of power signal before and after signal decomposition with the following properties:

1) signal at the output of the low-pass (LP) filter with cut-off frequency $f_1 = 0.005$. The aim of the filter is attenuation of the signal components above the frequency $f_1$ and extraction of the slow variable component (direct component (DC)). On the basis of the properties of the FT, it is shown that the mean value of the signal corresponds to the amplitude at the frequency $f = 0$ Hz. Therefore, the aim of the LP filter is extraction of the slowly changing average value. Such filters are frequently called as a moving average filter. If we assume that $x[n]$ is a generated power, and $x_{LP}[n]$ is a signal at the output of the LP filter, then we can show that

$$E(x[n]) = E(x_{LP}[n]) \tag{13}$$

i.e., the average value of the signal $x[n]$ is equal to average value of the signal $x_{LP}[n]$. This property is apparent from the analysis of the PDF of the signal $x_{LP}[n]$.

2) signal at the output of the band-pass filter with cut off frequency interval $[f_1, f_2) = [0.005, 0.05)$ Hz. The purpose of this filter is extraction of the information

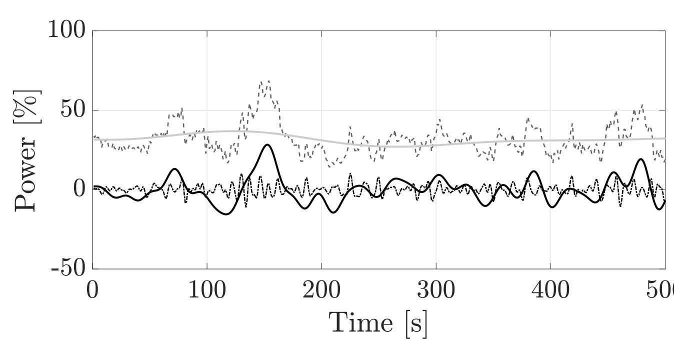


Fig. 13: Close-up of the power generated $x[n]$ (gray dashed), slow varying loads $x_{LP}[n]$ (light gray), medium varying loads $x_{BP_1}[n]$ (black) and fast varying loads $x_{BP_2}[n]$ (black dotted).

that is associated with the filter bandpass frequencies and attenuate other frequency components. This filter attenuates the signal component with frequency $f = 0$ Hz; therefore, the average value of the signal at the output of the filter $x_{BP_1}[n]$ is as follows:

$$E(x_{BP_1}[n]) = 0 \tag{14}$$

Property (14) implies that instantaneous values of the signal $x_{BP_1}[n]$ oscillates around zero, i.e., $x_{BP_1}[n]$ can have both positive and negative values. It is worth noting that the signal period is equivalent to $[1/f_1, 1/f_2) = [200, 20)$ s. In Table II, we show that the mean of the medium variable is 0.

3) signal at the output of the band-pass filter with cut off frequencies $[f_2, f_3] = [0.05, 0.2]$ Hz, whose aim is to extract of the fast variable signal component $x_{BP_2}[n]$. This filter also attenuates the frequency component at $f = 0$ Hz; this means:

$$E(x_{BP_2}[n]) = 0 \tag{15}$$

In addition, it is worth noting that the signal period is equivalent to $[1/f_2, 1/f_3] = [20, 4]$ s.

The analysis can be extended to identify distributions that best fit the data in order to extract generalizations; however this was beyond of the scope of the paper.

## VI. Practical application of the methodology

In section we present practical applications of the proposed methodology. The proposed methodology, based on signal decomposition, allows for extracting slowly varying operational loads and to quantify the variability from different frequencies. Quantified variability helps dimensioning a separate source of power to cover the power variability or to adjust the configuration and the size of generators. Adjusting the size of generators to cover slowly varying loads allow for more efficient operations and lets the engine run with more optimal specific fuel consumption (SFC) [g/kWh], which saves costs, reduces emissions and decreases maintenance.

### A. *Support in new power system design and optimization*

In the upper subplot of Fig. 14, we see the probability distribution function of power generated in the DP mode (left axis). The black dashed line shows a SFC (right axis) with the indicated optimal point of operation in terms of fuel efficiency and environmental pollution [56]. We observe that the concentration of low loads leads to inefficient engine operation and high fuel consumption. The proposed methodology can support the standard methods based on load factor analysis and can be applied to select a new engine size with more optimal operating point.

To illustrate an example of application, we assume that for further analysis, the installed power of the vessel is equal to 8000kW [34]. The support for a new power system design can based on the properties of the decomposed power signal, which are summarised in Table II. On the basis of the methodology, we propose the following minimum configuration of a new power system:

1) an engine operating at its optimal point, i.e., ensuring a possible minimum SFC, and which is used to cover loads associated with the slow variable component. From Fig. 14 and according to the described properties of the power signal, we propose to use an engine whose $MCR = 90\%$ will correspond to the maximum value of the slow variable component $x_{max} = 38.3\%$ of MCR of the power installed. If we assume that the installed power is 8000 kW, then the maximum power of the engine will be $0.383 \times 8000 = 3064$ kW, and the engine will produce the power within interval $[x_{min} \times 8000, x_{max} \times 8000]$ kW, i.e., $[1008, 3064]$ kW, which is equivalent to $[29, 90]\%$ of MCR. On average, the engine will work around $x_{mean} \times 8000$ kW, i.e., $2048$ kW $\equiv 60\%$ of MCR. There is a possibility to further move the optimal point toward a maximum of $100\%$ MCR;
2) a battery that will serve as a source of power to cover loads from a medium variable component. The medium variable component has positive values; this means that a battery will deliver the power and discharge as well as the medium variable component has negative values when battery will charge (see Fig. 13). The maximum value of the medium variable components, according to statistical analysis presented in Table II, is equal to $x_{max} = 33.7\%$ of MCR; this is equivalent to $0.337 \times 8000 = 2696$ kW. It is worth noting that the maximum time interval for the medium component is only 200 s; this means that in the worst case, the battery will have to provide 2696 kW for a maximum of 200 s. Therefore, the battery needs to have a minimum capacity of 150 kWh to cover medium variable loads. Because of a large amount of variations in power fluctuation, batteries can overheat and their life span is reduced [57]. This suggests that power signal decomposition gives us an indication that for loads associated with high frequencies, batteries are not the best solution and prompt us to use supercapacitors for rapidly

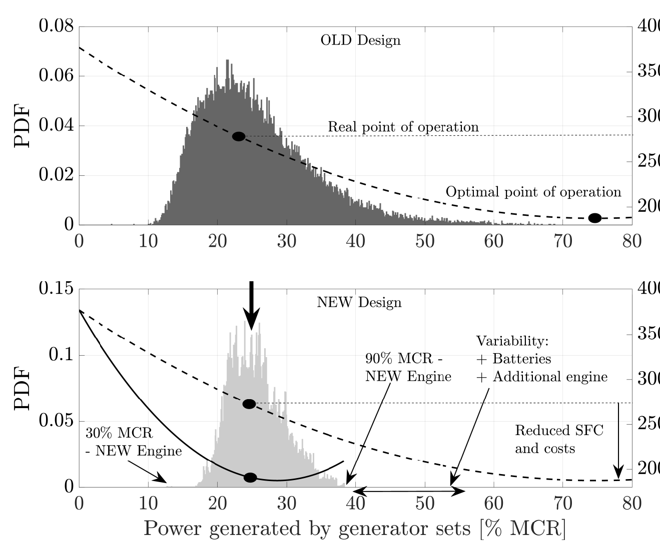


Fig. 14: Application of the proposed methodology for power system design improvement.

meeting power demands [31];

3) a supercapacitor, flywheel, or a battery that will serve as a source of power for a fast variable component. The fast variable component also oscillates around zero; therefore, in time, when it adopts negative values, it means that the energy source is being charged, while when the fast variable component adopts positive values, it means that the energy source discharge (see Fig. 13). The maximum value for the fast variable component, according to statistical analysis presented in Table II, is $x_{max} = 16.3\%$ of MCR, which corresponds to the power of $0.163 \times 8000 = 1304$ kW. The maximum period for which the battery will be providing the energy is 20 s. Therefore, to cover fast variable loads, there is a need for a supercapacitor with the minimum capacity of 7.2 kWh.

On the basis of the proposed methodology we achieved following benefits, see Fig. 14:

- originally, the engine operated at $[4.8\%, 68.8\%]$ of MCR range, with an average of $25.6\%$ MCR, see Table II. After power decomposition, the new engine can operate at $[29\%, 90\%]$ of MCR range with an average $60\%$ MCR. Such modification of the current design ensures that the engine operates at its optimal point of operation, thereby providing a reduced SFC of approximately 100 [g/kWh];
- dimensioning the engine to work constantly helps to keep environment safe and enable efficient operations;
- power decomposition based on frequency intervals allow to establish the minimum and maximum period of medium and fast variable loads that can be used for battery dimensioning.

Numerous applications of batteries are reported in [35], [58], [59], which show different potentials to improve performance of distribution systems in peak load shaving, load leveling, power quality improvements, and energy management applications. Batteries can also be used as a back-up power source, e.g., for powering the propulsion system for a short period of time to reposition the vessel [58].

In the case we would like to have the same power capacity as that in the previous design, e.g., to keep a large reserve of power required in DP condition for power supply vessel, we can install larger batteries as a spinning reserve or an additional engine. In this scenario, we do not adjust peak power designed by the load factor analysis and assure the vessel operability by keeping the installed power at the same value; however, we adjust the size of engines or configuration of new power plant. There are number of possible configurations based on the proposed methodology. By performing signal decomposition, the designer can adjust the number and size of generators and dedicate them to cover various load variability.

The proposed methodology can be used for dimensioning of the power system of similar vessels, a situation that is common in the industry when ship owners order a vessel fleet; it can also be used for vessel retrofit and to extend the knowledge of power systems in a dynamic environment. For the retrofit of the existing vessel, the proposed methodology helps to dimension the battery and adjust the energy management system to run the installed engine with optimal loads and use the battery when frequency of the loads changes. The benefit of power decomposition based on frequency analysis for battery dimensioning is that we know exactly the maximum time period required to supply the energy, and according to distribution of loads, we can find the maximum power which we need.

### B. Other practical applications

The analysis based on real measurements can be applied for:

- Power system design verification

The analysis of power generated in each vessel operation can be used in electric power load analysis for the dimensioning of the power plant and to define important specific modes and scenarios. The most important modes will be the ones where the vessel used the maximum power most frequently, or with a wide distribution of power. Applying the PDF and CDF analysis of real measurement helps to verify the maximum and mean values of electric power used in every mode of operation. This analysis allows power design verification, comparison of the electrical power load analysis based on the load factors, and is complementary. When the PDF analysis reveals that the maximum load and designed peak power is never used in reality and the design margin is too large, we can consider installing smaller engines on a new vessel, and e.g., batteries that will be used in extreme situations or as a safety reserve. As shown in Section III-A, in the DP mode, $99\%$ of time the power generated is below $40\%$ and the design margin is approximately $31\%$; in this mode, the design margin is a redundancy requirement. However, in similar way design margin can be verified in each operational mode.

- Validation of "sea-margin" in power system design

Another practical application of the proposed methodology is quantification of the variability from environmental conditions that can be used as a verification of the "sea-margin", which is applied as a safety factor on the top of the results from hydrodynamic simulations conducted for the calm sea in the power system design. The dynamic factor is often assumed during the electrical power load analysis by marine engineers, and currently, EPLA does not account for this. The assumption of the variability of the environmental conditions can result in overdimension of the power installation if the designer assume more variability than needed. In other situations, not assuming a dynamic environmental conditions can result in unavailability of power in dangerous situations. The variability from varying sea conditions for the analyzed vessel was equal to $IQR_m$=21.5% of MCR, and this can be used as a validation of applied assumptions and to improve simulations of steady-state scenarios.

## VII. CONCLUSIONS

In this paper, we have demonstrated techniques for the exploration of data from the vessel on-board monitoring system, based on the one-year measurements from the PSV. Analysis, based on the probability distribution function (PDF), enabled us to observe the most common loads and maximal loads whilst the cumulative distribution functions (CDF) allowed us to see the amount of time spent in specific load intervals. This information can be an input for the power system design verification, optimization, and new system design requirements by establishing real design margins and investigating high power demands, resulting in PDF tails.

In order to improve our understanding of properties of power signal, we proposed and described a data-driven methodology where the power is decomposed based on different frequency bands. Power variability, associated with frequency bands, was linked with the environmental conditions that the vessel is exposed to as well as with the frequency of electrical loads from the power system. The properties of decomposed power enable better understanding of probability distributions of a power signal tails and to improve the power system design of new vessel.

Statistical analysis of decomposed power enable to dedicate a separate source of power to cover loads associated with different frequency bands, e.g., engine that covers slowly varying loads; batteries and supercapacitors that serve as a source of power for medium and fast varying loads. The association of statistical properties of decomposed signals with the properties of signals in the time domain allows for dimensioning, e.g., batteries that are alternately charged and discharged during the operation of the power system. The analysis allow to dimension more efficient, hybrid power systems, for various types of vessels with special operational profile, e.g. offshore, naval, fishing vessels or ferries.

## Abbreviations

$ABS$ - American Bureau of Shipping
$BP$ - Band-pass (filter)
$CDF$ - Cumulative Distribution Function
$CPSD$ - Cross-Power Density Function
$DDS$ - Design Data Sheet
$DNV\text{-}GL$ - Det Norske Veritas-Germanischer Lloyd
$DP$ - Dynamic Positioning
$EPLA$ - Electric Power Load Analysis
$FT$ - Fourier Transform
$FIR$ - Finite Impulse Response
$IMO$ - International Maritime Organization
$IQR$ - Interquartile Range
$IQR_m$ - Interquartile Range Modified
$LP$ - Low-pass (filter)
$LR$ - Lloyd's Register
$NA$ - National Authorities
$MCR$ - Maximum Coninuous Rating
$PSV$ - Platform Supply Vessel
$PDF$ - Probability Density Function
$PSD$ - Power Spectral Density
$SFC$ - Specific Fuel Consumption

## Acknowledgment

Authors wish to thank the Golden Energy Offshore and acknowledge support from Professor H.Langseth and experts of marine power systems from Rolls-Royce, especially R.Kleppe, H.M. Hjørungnes, as well as for comments and valuable discussions from dr R.I Stephens, and dr Y.Wang.

## References

[1] M. R. Patel, *Shipboard Electrical Power Systems*. Taylor & Francis Group, 2012.
[2] *IEC 61892, Mobile and Fixed Offshore Units - Electrical installations*, International Electrotechnical Commission Std., 2015.
[3] *IEEE Recommended Practice for Electric Installations on Shipboard*, Std. IEEE 45-2002 (Revision of IEEE Std 45-1998), Oct 2002.
[4] *IEC 60092 series Electrical Installations in Ships*, International Electrotechnical Commission Std.
[5] DNVGL, *Recommended Practice. Dynamic positioning vessel design philosophy guidelines*, rp-e306 ed., July 2015.
[6] ——, *Recommended Practice. Dynamic positioning systems - operation guidance*, rp-e307 ed., July 2015.
[7] T. I. Bø, A. R. Dahl, T. A. Johansen, E. Mathiesen, M. R. Miyazaki, E. Pedersen, R. Skjetne, A. J. Sørensen, L. Thorat, and K. K. Yum, "Marine vessel and power plant system simulator," *IEEE Access*, vol. 3, pp. 2065–2079, 2015.
[8] T. A. Johansen, T. I. Bø, E. Mathiesen, A. Veksler, and A. J. Sørensen, "Dynamic positioning system as dynamic energy storage on diesel-electric ships," *IEEE Transactions on Power Systems*, vol. 29, no. 6, pp. 3086–3091, Nov 2014.
[9] M. Falahi, K. L. Butler-Purry, and M. Ehsani, "Reactive power coordination of shipboard power systems in presence of pulsed loads," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3675–3682, Nov 2013.
[10] A. Swider, S. Skjong, and E. Pedersen, "Complementarity of data-driven and simulation modeling based on the power plant model of the offshore vessel," in *International Conference on Offshore Mechanics and Arctic Engineering*, vol. 7B: Ocean Engineering, no. OMAE2017-62027, 06 2017. [Online]. Available: http://dx.doi.org/10.1115/OMAE2017-62027
[11] S.-J. Huang and K.-R. Shih, "Short-term load forecasting via arma model identification including non-gaussian process considerations," *IEEE Transactions on Power Systems*, vol. 18, no. 2, pp. 673–679, May 2003.
[12] M. Hanmandlu and B. K. Chauhan, "Load forecasting using hybrid models," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 20–29, Feb 2011.
[13] J. Wolfe and M. J. Roa, "Advanced methods for tabulation of electrical loads during special modes of marine vessel operation," *IEEE Transactions on Industry Applications*, vol. 53, no. 1, pp. 667–674, Jan 2017.
[14] N. Doerry, "Electric power load analysis," *Naval Engineers Journal*, vol. 124, pp. 45–48, Dec. 2012.
[15] N. S. S. C. NAVSEA, *Design Data Sheet: Electrical Power Load Analysis (EPLA) for Surface Ships (DDS 310-1), Rev. 1,*, Department of the Navy, Washington Navy Yard, DC, 17 September 2012.
[16] J. M. Wolfe and M. M. Fanberg, "Statistical analysis for shipboard electrical power plant design," in *Proc. SNAME 2013, Annual Meeting & Expo.,*, 2013.
[17] U. Orji, B. Sievenpiper, K. Gerhard, S. B. Leeb, N. Doerry, J. L. Kirtley, and T. McCoy, "Load modeling for power system requirement and capability assessment," *IEEE Transactions on Power Systems*, vol. 30, no. 3, pp. 1415–1423, May 2015.
[18] I. Hatzilau, G. Tsekouras, J. Prousalidis, and I. Gyparis, "On electric load characterization and categorization in ship electric installations," in *Institute of Marine Engineering, Science and Technology - INEC 2008: Embracing the Future*, 2008.
[19] J. M. Prousalidis, G. J. Tsekouras, and F. Kanellos, "New challenges emerged from the development of more efficient electric energy generation units," in *2011 IEEE Electric Ship Technologies Symposium*, April 2011, pp. 374–381.
[20] C. L. Su and C. H. Liao, "Ship electrical load analysis considering power generation efficiency," in *2015 IEEE/IAS 51st Industrial Commercial Power Systems Technical Conference (I CPS)*, May 2015, pp. 1–11.
[21] H. Chin, C. Su, and C. Liao, "Estimating power pump loads and sizing generators for ship electrical load analysis," *IEEE Transactions on Industry Applications*, vol. 52, no. 6, pp. 4619–4627, Nov 2016.
[22] A. Boveri, P. Gualeni, D. Neroni, and F. Silvestro, "Stochastic approach for power generation optimal design and scheduling on ships," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Sept 2017, pp. 1–6.
[23] P. B. Backlund, C. C. Seepersad, and T. M. Kiehne, "All-electric ship energy system design using classifier-guided sampling," *IEEE Transactions on Transportation Electrification*, vol. 1, no. 1, pp. 77–85, June 2015.
[24] A. K. Ådnanes, "Maritime electrical installations and diesel electric propulsion," ABB AS, Tech. Rep., 2003.

[25] G. J. Tsekouras, I. S. Karanasiou, and F. D. Kanellos, "Classification of total load demand profiles for war-ships based on pattern recognition methods," in *Proceedings of the 5th WSEAS International Conference on Communications and Information Technology*, ser. CIT'11. Stevens Point, Wisconsin, USA: World Scientific and Engineering Academy and Society (WSEAS), 2011, pp. 316–322. [Online]. Available: http://dl.acm.org/citation.cfm?id=2028497.2028555

[26] G. Tsamopoulos, N. Giannitsas, F. D. Kanellos, G. J. Tsekouras, and I. S. Karanasiou, "Load estimation for war-ships based on pattern recognition methods," *Journal of Computations & Modelling*, vol. 4, no. 1, pp. 207–222, 2014.

[27] G. J. Tsekouras, I. K. Hatzilau, and J. M. Prousalidis, "A new pattern recognition methodology for classification of load profiles for ships electric consumers," *Journal of Marine Engineering & Technology*, vol. 8, no. 2, pp. 45–58, 2009. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/20464177.2009.11020222

[28] G. Chicco, R. Napoli, and F. Piglione, "Load pattern clustering for short-term load forecasting of anomalous days," in *2001 IEEE Porto Power Tech Proceedings (Cat. No.01EX502)*, vol. 2, 2001, pp. 6 pp. vol.2–.

[29] G. J. Tsekouras, N. D. Hatziargyriou, and E. N. Dialynas, "Two-stage pattern recognition of load curves for classification of electricity customers," *IEEE Transactions on Power Systems*, vol. 22, no. 3, pp. 1120–1128, Aug 2007.

[30] G. Tsekouras, P. Kotoulas, C. Tsirekis, E. Dialynas, and N. Hatziargyriou, "A pattern recognition methodology for evaluation of load profiles and typical days of large electricity customers," *Electric Power Systems Research*, vol. 78, no. 9, pp. 1494 – 1510, 2008. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378779608000278

[31] M. Zarghami, M. Y. Vaziri, A. Rahimi, and S. Vadhva, "Applications of battery storage to improve performance of distribution systems," in *2013 IEEE Green Technologies Conference (GreenTech)*, April 2013, pp. 345–350.

[32] G. J. Tsekouras, F. D. Kanellos, and J. Prousalidis, "Simplified method for the assessment of ship electric power systems operation cost reduction from energy storage and renewable energy sources integration," *IET Electrical Systems in Transportation*, vol. 5, no. 2, pp. 61–69, 2015.

[33] E. Skjong, T. A. Johansen, M. Molinas, and A. J. Sørensen, "Approaches to economic energy management in diesel-electric marine vessels," *IEEE Transactions on Transportation Electrification*, vol. 3, no. 1, pp. 22–35, March 2017.

[34] H. E. Lindstad, G. S. Eskeland, and A. Rialland, "Batteries in offshore support vessels - pollution, climate impact and economics," *Transportation Research Part D: Transport and Environment*, vol. 50, pp. 409 – 417, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1361920916302723

[35] V. Shagar, S. G. Jayasinghe, and H. Enshaei, "Effect of load changes on hybrid shipboard power systems and energy storage as a potential solution: A review," *Inventions*, 2017. [Online]. Available: http://www.mdpi.com/2411-5134/2/3/21

[36] T. I. Bø, "Scenario- and optimization- based control of marine electric power systems," Ph.D. dissertation, Norwegian University of Science and Technology, 2016.

[37] S. Kay, *Intuitive Probability and Random Processes using MATLAB*. Springer, 2005.

[38] T. I. Fossen, *Marine Control Systems. Guidance, Navigation, and Control of Ships, Rigs and Underwater Vehicles.* Marine Cybernetics AS, 2002.

[39] W. Munk, "Origin and generation of waves," *Coastal Engineering Proceedings*, vol. 1, no. 1, pp. 1–4, 1950. [Online]. Available: https://icce-ojs-tamu.tdl.org/icce/index.php/icce/article/view/904

[40] W. Pieson and J. L. Moskowitz, "A proposed spectral form for fully developed wind seas based on the similarity theory of s. a. kitaigorodskii," *Journal of Geophysical Research*, vol. 69, no. 24, pp. 5181–5190, 1964.

[41] D. E. Hasselmann, M. Dunckel, and J. A. Ewing, "Directional wave spectra observed during jonswap 1973," *Journal of Physical Oceanography*, vol. 10, no. 8, pp. 1264–1280, 1980. [Online]. Available: https://doi.org/10.1175/1520-0485(1980)010¡1264:DWSODJ¿2.0.CO;2

[42] M. K. Ochi, *Ocean Waves: The Stochastic Approach*, ser. Cambridge Ocean Technology Series. Cambridge University Press, 1998.

[43] H. E. Krogstad and O. A. Arntsen, *Linear wave theory*. Nowergian University of Science and Technology, 2000.

[44] G. Rodríguez, C. G. Soares, and M. Pacheco, "Wave period distribution in mixed sea-states," *Journal of Offshore Mechanics and Arctic Engineering*, vol. 126(1), pp. 105–112, 2004.

[45] S. K. Mitra, *Digital Signal Processing*, 4th ed. McGraw-Hill, 2010.

[46] S. M. Kay, *Fundamentals of Statistical Signal Processing, Volume III: Practical Algorithm Development*. Prentice Hall, 2013.

[47] ——, *Modern Spectral Estimation: Theory and Application*. Prentice Hall, 1999.

[48] M. H. Hayes, *Statistical Digital Signal Processing and Modeling*. Wiley, 1996.

[49] S. Kay, *Fundamentals of Statistical Signal Processing, Volume II: Detection Theory*. Prentice Hall, 1998.

[50] U. Spagnolini, *Statistical Signal Processing in Engineering*, 1st ed. Wiley, 2018.

[51] L. L. Scharf, *Statistical Signal Processing: Detection, Estimation, and Time Series Analysis*, 1st ed. Pearson, 1991.

[52] J. S. Bendat and A. G. Piersol, *Random Data: Analysis and Measurement Procedures*, 4th ed. Wiley, 2010.

[53] A. Swider and E. Pedersen, "Influence of loss of synchronisation between signals from various marine systems on robustness of predictive model algorithms," in *Smart Ship Technology, London, UK*. The Royal Institution of Naval Architects, 2017.

[54] A. Papoulis and S. U. Pillai, *Probability, Random Variables and Stochastic Processes*, 4th ed. McGraw-Hill Europe, 2002.

[55] S. Dowdy, S. Wearden, and D. Chilko, *Statistics for Research*. Wiley-Interscience, 2004.

[56] P. Michalopoulos, J. M. Prousalidis, G. J. Tsekouras, and F. D. Kanellos, "Comparison of ship power systems from an optimal economic operation point of view," in *2015 IEEE Electric Ship Technologies Symposium (ESTS)*, June 2015, pp. 256–260.

[57] T. I. Bø and T. A. Johansen, "Battery power smoothing control in a marine electric power plant using nonlinear model predictive control," *IEEE Transactions on Control Systems Technology*, vol. 25, no. 4, pp. 1449–1456, July 2017.

[58] E. Skjong, R. Volden, E. Rødskar, M. Molinas, T. A. Johansen, and J. Cunningham, "Past, present, and future challenges of the marine vessel's electrical power system," *IEEE Transactions on Transportation Electrification*, vol. 2, no. 4, pp. 522–537, Dec 2016.

[59] V. Shagar, S. Gamini, and H. Enshaei, "Effect of load changes on hybrid electric ship power systems," in *2016 IEEE 2nd Annual Southern Power Electronics Conference (SPEC)*, Dec 2016, pp. 1–5.


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