Ship performance and navigation data compression and communication under autoencoder system architecture

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Abstract

Modern vessels are designed to collect, store and communicate large quantities of ship performance and navigation information through complex onboard data handling processes. That data should be transferred to shore based data centers for further analysis and storage. However, the associated transfer cost in large-scale data sets is a major challenge for the shipping industry, today. The same cost relates to the amount of data that are transferring through various communication networks (i.e. satellites and wireless networks), i.e. between vessels and shore based data centers. Hence, this study proposes to use an autoencoder system architecture (i.e. a deep learning approach) to compress ship performance and navigation parameters (i.e. reduce the number of parameters) and transfer through the respective communication networks as reduced data sets. The data compression is done under the linear version of an autoencoder that consists of principal component analysis (PCA), where the respective principal components (PCs) represent the structure of the data set. The compressed data set is expanded by the same data structure (i.e. an autoencoder system architecture) at the respective data center requiring further analyses and storage. A data set of ship performance and navigation parameters in a selected vessel is analyzed (i.e. data compression and expansion) through an autoencoder system architecture and the results are presented in this study. Furthermore, the respective input and output values of the autoencoder are also compared as statistical distributions and sample number series to evaluate its performance.

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1. Introduction

1.1. Performance and navigation data

The ship energy efficiency management plan (SEEMP) [1], i.e. a mandatory requirement, enforces vessels to collect ship performance and navigation information by implementing various onboard sensors and data acquisition (DAQ) systems. These DAQ systems are designed to collect, store and communicate large quantities of ship performance and navigation information through complex data handling processes. Those are also facilitated by integrated bridge systems (IBSs), where various navigation and automation systems are connected [2]. These DAQ systems can create large-scale data sources and introduce additional challenges in onboard data handling processes. The same issues have often been identified as "Big Data" challenges by various industrial applications due to their volume, variety, veracity and velocity considerations [3]. Such big data sets can also create additional challenges during data transmission processes (i.e. between vessels and shore based data centers). e.g. the associated costs to transfer of such data sets through various satellite networks are relatively expensive in shipping. Hence, effective approaches to reduce the amount of data that communicate through such satellite networks are considered by the shipping industry in recent years and that reduce the associated data transfer costs.

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In general, the most preferred method by the shipping industry is to increase the length of the sampling period (i.e. a lower sampling rate) in which reduces the number of data samples collected with a selected time period. This method reduces the size of ship performance and navigation data sets, therefore the associated data transfer costs can be minimized. However, such data sets may not consist of all relevant information on ship performance and navigation conditions due to the lower data sampling rate. Furthermore, that can introduce additional challenges in parameter estimation processes [4], where estimation algorithms can diverge from the actual values due to inadequate data sampling rates. Therefore, the actual performance and navigation parameters cannot be estimated from such data sets in some situations. e.g. the engine fuel and power consumption values in vessels cannot be compared, adequately due to the lower sampling rate of the data sets.

1.2. Recent studies

Various ship performance and navigation monitoring systems with sensors and DAQs are implemented by the shipping industry. These on-board systems as a part of IBSs collect various ship performance and navigation parameters from navigation and automation systems. The same parameters (i.e. collect as big data sets) represent ship operational and navigation information that can be used under various decision support systems. These systems can often be divided into two categories of safety and performance monitoring systems. The safety monitoring systems focus on improving the navigation safety in shipping. Ship on-board systems to improve the navigation safety under rough weather conditions are presented in [6] and [7]. In addition, ship collision avoidance systems with decision support features are presented [8–12]. The performance monitoring systems focus on improving energy efficiency and reducing emissions in shipping [5]. Similarly, ship on-board systems to improve vessel energy efficiency under various operational conditions are presented by the authors in [13–15].

However, these systems have not been designed to handle big data sets and that may limit to small or moderate data sets. Therefore, the decision support features in such systems may often suffer under large scale ship performance and navigation data sets. This study proposes a methodology as a part of both safety and performance monitoring systems to overcome the same challenges in shipping. The methodology consists of pre-processing of ship performance and navigation data sets, where the size of data sets is reduced. Therefore, the resulted data sets can be conveniently transferred to shore based data centers in a reduced format. One should note that the proposed pre-processing step consists of implementing a dimensionality reduction method on ship performance and navigation data sets. Furthermore, the structure for ship performance and navigation data is discovered through the same method and used to reduce the size of the respective data sets (i.e. dimensionality reduction method or data compression). Even though the size of the respective

data set is reduced, the amount of ship performance and navigation information is preserved (i.e. or approximately equal) during this data compression process. Since the size of the data sets can be reduced, the sampling rate of the same can be increased. Therefore, the information quality of ship performance and navigation data sets can be further improved.

1.3. Autoencoder

The proposed approach consists of implementing an autoencoder system architecture in an onboard data handling system that collects ship performance and navigation information. The autoencoder system architecture introduces a dimensionality reduction method, i.e. while preserving the amount of ship performance and navigation information, for the same data sets as the main contribution of this study. An overview of an autoencoder system architecture is presented in Fig. 1 consisting data compression, communication and expansion steps. Autoencoder is an unsupervised learning method that is implemented as a feed-forward neural network ([16] and [17]), which is also categorized as the linear version of deep learning [18]. Autoencoders are the fundamental building blocks of deep learning and that may associate with additional linear and/or nonlinear functions. Such autoencoders are capable to compress and expand the respective information that is the inputs to the same. Deep learning consists of learning the respective information from the bottom layer of the neural network rather than the top layer (i.e. back-propagation approach). Hence, that can be a slight deviation from conventional neural network approaches. However, this approach is illustrated as a better learning method for neural networks by the recent studies of other transport systems [19]. Since this study focuses on the linear version of deep learning, the proposed neural networks consists of a linear function (i.e. under the proposed autoencoder system architecture). In general, the autoencoder recreates the input of the neural network at its output. The neural networks consist of hidden layers to compress and expand the respective data and the hidden layers locate between the input and output layers of the autoencoder (see Fig. 1). The difference between the input (i.e. the actual parameters) and output (i.e. the estimated parameters) data sets can be used to evaluate the success of the neural network (i.e. the comparison/expansion accuracy).

An autoencoder system architecture consists of two sections (see Fig. 1): encoder and decoder. The inputs to the encoder are ship performance and navigation data collected from various onboard sensors. The input data sets are compressed by the encoder under the respective linear function of the autoencoder (i.e. the hidden layer compresses the data sets). Then, the compressed data sets are transmitted through communication networks to shore based data centers for storage and further analyses. The compressed data sets are received by the decoder of the autoencoder located in shore based data centers, where the data sets are expanded (see Fig. 1) under the same linear function of the autoencoder. Therefore, the outputs of the decoder consist of estimated ship performance and navigation data sets. These data sets
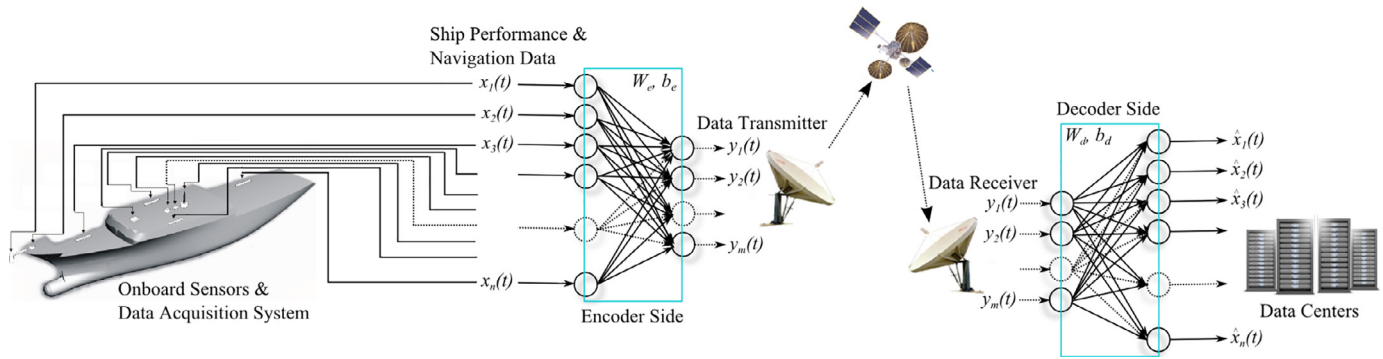
Fig. 1. Autoencoder system architecture.

(i.e. estimated ship performance and navigation information) can further be analyzed for other applications, i.e. ship energy efficiency, emission, and system reliability, at the respective data centers. The measured and estimated ship performance and navigation data sets may have some parameter variations that reflect the autoencoder performance. However, some erroneous conditions can also be introduced into the same data set during this process (i.e. data compression and expansion) and that may relate to the respective linear function. Therefore, an appropriate linear function should be assigned under the autoencoder system architecture. One should note that an autoencoder system architecture (i.e. the encoder and decoder) facilitates to extract a low dimensional high-level representation from a high-dimensional ship performance and navigation data sets. It is believed that such representation can also be used to evaluate the respective ship performance and navigation conditions. Furthermore, the same (i.e. a low dimensional high-level representation) can also be expanded back to the high-dimensional ship performance and navigation data sets set by considering the respective linear function of the autoencoder. Hence, the respective linear function under data compression/expansion steps of an autoencoder plays an important role.

Autoencoders that are also a part of deep learning are often associated with various linear and nonlinear approaches that relate to the respective application domains [20]. Liner approaches consist of real, complex and finite field applications of autoencoders. Nonlinear approaches consist of Boolean, Boolean/linear, neural networks and Boltzmann machines applications of autoencoders. However, linear approaches consist of linear functions for both encoder and decoder sides and this study also focuses on the same. This linear function proposed in this study for the autoencoder system architecture is derived from principal component analysis (PCA) and the respective derivation of this function is also presented in the following sections. One should note that the linear function under PCA represents a set of vectors, i.e. singular values and vectors, and these vectors relate to the structure of the ship performance and navigation data set. Hence, such structural information, i.e. principal components, in the ship performance and navigation data set is used for both compression and expansion steps of the autoencoder. One should

note that the data structure represents various relationships among the respective ship performance and navigation parameters. Those parameters relate to onboard sensors of the vessels, therefore the data structure can represent an abstract model of the vessel and ship systems. Since vessels consist of possible combinations of different automation and navigation systems, such data structures should further be investigated to understand vessel and ship system behavior.

1.4. Principal component analysis

PCA is a non-parametric method for extracting relevant information from data sets. That transforms the parameter set, i.e. sensor measurements, of the respective data into a linearly uncorrelated parameter set, i.e. the new basis, which can be used as a low dimensional representation of the original data set. The linearly uncorrelated parameters of the data set may improve the content visibility in some situations, because those represent the most important parameter relationships, i.e. the correlations among parameters, in the data set. One should note that the new basis, i.e. the linearly uncorrelated parameters, is represented by the respective principal components (PCs), i.e. singular values and vectors, of the data set. Singular values and vectors are fundamental building blocks of multi input multiple-input and multiple-output electrical and mechanical systems accordance with the system theory. The respective PCs that have a linear combination of the respective ship performance and navigation parameters are derived from the sensor measurements. The encoder and decoder of the autoencoder are based on these PCs. The number of PCs that should implement under the hidden layers, i.e. the encoder and decoder, of the autoencoder should be selected, appropriately by considering the respective application. Such selection should be made by considering the singular values and that represent the percentage of the information content of the parameter relationships in the data set. Furthermore, the respective number of PCs relate to the number of nodes in the hidden layers of the autoencoder, where the most important information in the data set should be preserved. Hence, this approach reduces the dimensionality of ship performance and navigation data set by considering its structure (i.e. PCs). Furthermore, the same PCs can be used to visualize ship per-

formance and navigation data under a different set of parameters, where the information visibility can be improved. Finally, the reduced data sets of ship performance and navigation information communicate through satellite networks, where the respective transfer costs can be minimized.

There are several steps that should be taken on the data sets, prior to implementing PCA. Firstly, any erroneous regions (i.e. sensor faults and noise and system abnormal events) in the data sets should be removed to improve the data integrity, if possible. Furthermore, slow maneuvering situations of the vessels should be removed from the respective ship performance and navigation data sets, therefore low signal-to-noise ratio situations can be avoided. Secondly, the scaling of ship performance and navigation data sets should be done to reduce uneven parameter contributions during PCA. e.g. the parameters with large variances may have bigger contributions in the data analysis and that should be avoided. Such situations can be avoided by standardizing the respective parameters in ship performance and navigation data sets, where each parameter is assigned with zero mean and 1.0 variance values. Hence, each parameter has an equal variance (i.e. 1.0), therefore that influences equally in PCA [21]. Even though a set of unit-less parameters are introduced into PCA by this step, the respective units can be preserved, separately [22]. However, this approach may increase sensor noise in some situations and that degrades the outcome of PCA. That is another reason to remove slow vessel maneuvering situations (i.e. high sensor noise situations) from the respective ship performance and navigation data sets, as mentioned before.

Each PC represents an important variance direction that is orthogonal to each succeeding variance. The top principal component represents the largest variance direction and the bottom principal component represents the smallest variance direction of the data set. The most important PCs (i.e. the top PCs) in a data set can be selected to represent the entire data set, i.e. a lower dimensional representation that is defined as data compression in this study. An accumulated percentage of variances (i.e. the summation of the respective singular values) in the data set can be used as a guideline to select the most important PCs. Therefore, a higher percentage of the information on ship performance and navigation data can be preserved by selecting an appropriate number of PCs.

Additional advantages have also been noted by selecting an appropriate number of PCs. It is observed that data anomalies are often grouped into the bottom principal components, therefore the bottom PCs can also be used to identify such erroneous data regions [23]. The respective erroneous regions, i.e. data anomalies, can be isolated and recovered in some situations to improve the quality of ship performance and navigation data by considering the respective PCs. Furthermore, redundant parameters (i.e. redundant sensor measurements) within the data sets can also be identified by observing the PCs. Therefore, PCA has often been adopted by many "Big Data" applications in various industrial platforms [24] as a part of their data handling processes.

2. Mathematical formulation

2.1. Autoencoder development

A mathematical overview of an autoencoder with respect to PCA is presented in this section. The encoder compresses the measured data set of ship performance and navigation parameters as mentioned before. The input to the encoder is $X(t)$, i.e. a measured ship performance and navigation data set, denoted as:

$$X(t) = \begin{bmatrix} x_1(t) & x_2(t) & \ldots & x_n(t) \end{bmatrix} \qquad (1)$$

where $x_1(t), x_2(t), \ldots, x_n(t)$ with $x_i(t) \in R^d$ represent the respective ship performance and navigation parameters. One should note that $X(t)$ should a normalized data set derived from actual ship performance and navigation parameters. The output of the encoder is $Y(t)$, a compressed data set, denoted as:

$$Y(t) = \begin{bmatrix} y_1(t) & y_2(t) & \ldots & y_m(t) \end{bmatrix} \qquad (2)$$

where $n > m$ and $y_1(t), y_2(t), \ldots, y_m(t)$ with $y_i(t) \in R^d$ represent a set of new parameters that are derived from the measured ship performance and navigation data set by considering PCA. The compressed data set, $Y(t)$, may consist of less parameters than the actual data set, $X(t)$, due to the selected number of PCs. It is expected that the compressed data set is delivered to data centers through the respective communication networks. The encoder of this neural network (i.e. the data compression) can be denoted as:

$$Y(t) = f_e(W_e X(t) + b_e) \qquad (3)$$

where $f_e(\cdot)$ is the respective linear function, W_e is the weight matrix and b_e is the bias vector of the encoder. On the other hand, the decoder expands the compressed data set of ship performance and navigation parameters. The output of the decoder side is $\hat{X}(t)$, the data set of estimated ship performance and navigation parameters denoted as:

$$\hat{X}(t) = \begin{bmatrix} \hat{x}_1(t) & \hat{x}_2(t) & \ldots & \hat{x}_n(t) \end{bmatrix} \qquad (4)$$

where $\hat{x}_1(t), \hat{x}_2(t), \ldots, \hat{x}_n(t)$ with $\hat{x}_i(t) \in R^d$ represent a set of estimated ship performance and navigation parameters. The decoder of this neural network (i.e. the data expansion) can be written as:

$$\hat{X}(t) = f_d(W_d Y(t) + b_d) \qquad (5)$$

where $f_d(\cdot)$ is the respective linear function, W_d is the weight matrix and b_d is the bias vector of the decoder. One should note that $f_e(\cdot)$ and $f_d(\cdot)$ can either be linear or nonlinear functions. However, a linear function is considered in this study as mentioned before. The actual data set in ship performance and navigation information is normalized with zero mean and 1.0 variance values (i.e. $b_e \approx b_d \approx 0$), previously. Hence, the respective encoder and decoder functions in (3) and (5) can be simplified as:

$$Y(t) = W_e X(t)$$
$$\hat{X}(t) = W_d Y(t) \tag{6}$$

Considering (6), the data compression and expansion steps can be summarized as:

$$\hat{X}(t) = W_d W_e X(t) \tag{7}$$

Therefore, (7) represents an expression between the actual and estimated data sets of ship performance and navigation parameters. One should note that some variations in the actual and estimated data sets can be observed under the data compression and expansion steps. Such parameter variations introduce some erroneous conditions that can be denoted by:

$$E(t) = \begin{bmatrix} e_1(t) & e_2(t) & \dots & e_n(t) \end{bmatrix} \tag{8}$$

where $e_1(t), e_2(t), \dots, e_n(t)$ with $e_i(t) = x_i(t) - \hat{x}_i(t), \in R^d$ represent a set of ship performance and navigation parameter errors. Considering (7), (8) can be written as:

$$E(t) = X(t) - \hat{X}(t) = (I - W_d W_e)X(t) \tag{9}$$

If $W_e \approx W_d^T$, then $W_d W_e = W_d W_d^T \approx I$ and (9) can be written as:

$$E(t) \approx 0 \tag{10}$$

Therefore, W_e can be derived from W_d to minimize the errors between the measured and estimated ship performance and navigation parameters. One should note that $W_e \approx W_d^T$ is considered to approximate measured and estimated ship performance and navigation parameters. Hence, the weight matrix, W_d, should further be calculated and denoted as:

$$W_d = \begin{bmatrix} w_1 & w_2 & \dots & w_n \end{bmatrix} \tag{11}$$

where $w_1, w_2, \dots, w_n$ with $w_i \in R^m$ represent the respective parameters in the weight matrix.

2.2. Principal component calculations

The respective errors between actual and estimated ship performance and navigation parameters should be minimized under the weight matrix of the autoencoder. Hence, the respective orthonormal basis of $E(t)$ that minimizes the mean least square error can be calculated by the following minimization problem:

$$Min. \|E(t)\|^2 = Min. \left\| X(t) - \hat{X}(t) \right\|^2$$
$$= Min. \left\| X(t) - W_d W_d^T X(t) \right\|^2 \tag{12}$$

The minimization problem in (12) can be also written as:

$$Min \sum_{i=1}^{n} \left\| x_i(t) - \hat{x}_i(t) \right\|^2 = Min. \, trace\left[(I - W_d W_d^T) X(t) X^T(t) \right] \tag{13}$$

One should note that (13) can be modified as the following maximization problem:

$$Min \sum_{i=1}^{n} \left\| x_i(t) - \hat{x}_i(t) \right\|^2 \Rightarrow Max. \, trace\left[W_d^T X(t) X^T(t) W_d \right] \tag{14}$$

Considering the method of Lagrange multipliers, (14) can be modified as:

$$L = trace\left[W_d^T X(t) X^T(t) W_d \right] + trace\left[(I - W_d W_d^T) \Lambda \right] \tag{15}$$

where $\Lambda = \Lambda^T \in R^{d \times d}$ is the Lagrange multiplier matrix. The gradient of (15) is zero at its stationary points. These stationary points represent the respective solutions to (14) and that can be written as:

$$X^T(t) X(t) W_d = W_d \Lambda$$
$$W_d W_d^T = I \tag{16}$$

Hence, (16) satisfy the required conditions in (10) and the objective function in (16) can also be denoted as:

$$W_d^T X^T(t) X(t) W_d = \Lambda \tag{17}$$

One should note that the Lagrange multiplier matrix, Λ, is selected as a diagonal matrix, which is also symmetric. Since the Lagrange multiplier matrix is a symmetric diagonal matrix that also represents the eigenvalues of $X^T(t)X(t)$ [25]. The top and bottom eigenvalues and eigenvectors of $X^T(t)X(t)$ is same as the top and bottom singular values and vectors of $X(t)$. Hence, the singular value decomposition (SVD) for the measured data set of ship performance and navigation parameters, $X(t)$, is considered to derive the Lagrange multiplier matrix. The respective SVD of the same data set can be written as:

$$X(t) = U \Sigma V^T \tag{18}$$

where Σ is the singular value matrix and U and V are the respective left and right singular vectors. Hence, the SVD of the data set gives the optimal solution to the minimization problem in (13). One should note that the left-singular vectors of $X(t)$ are the eigenvectors of $X(t)X^T(t)$ and the right-singular vectors of $X(t)$ are the eigenvectors of $X^T(t)X(t)$. The non-zero singular values of $X(t)$ are the square roots of the non-zero eigenvalues of both $X(t)X^T(t)$ and $X^T(t)X(t)$. Hence, the respective PCs of the ship performance and navigation data sets can be calculated by SVD as an efficient algorithm. These singular values and vectors that represent the PCs are orthogonal to each other. One should note that the same approach minimizes the least mean square reconstruction error and maximizes the projection variance between the input and output data sets of ship performance and navigation parameters. The top PC (i.e. the vector with the highest singular value) represents the largest variance and the bottom PC (i.e. the vector with the lowest singular value) represents the smallest variance that is orthogonal. Hence, the respective weight matrix is selected as:

$$W_d \equiv U \Sigma \tag{19}$$

By considering (19), the respective encoder and decoder functions, $f_e(\cdot)$ and $f_d(\cdot)$, can be derived.

2.3. Optimal values

Considering (19), (6) can be modified as:

$$Y(t) = \underbrace{(\Sigma_t)^{-1} U_t^T}_{=W_e} X(t) \tag{20}$$

where W_e is the modified weight matrix that consists of the respective singular values and vectors. Furthermore, Σ_t and U_t represent the matrices that consist of the top h-number of singular values and vectors (i.e. PCs) from Σ and U, respectively. One should note that (20) represents the linear function of the data compression step (i.e. the encoder side) of the autoencoder. The modified weight matrix is introduced by assuming that the most important information on the data set (i.e. ship performance and navigation parameters) is preserved by the respective singular values and vectors. It is expected that 95−99% of the ship performance and navigation information of the data set should be preserved during this compression and expansion steps of the autoencoder. That can be done by selecting an appropriate set of PCs (i.e. singular values and vectors) from the respective data set. Considering a situation, where $\alpha\%$ of the variance should be retained within the selected PCs, the respective singular value calculation can be written as:

$$1 - \sum_{i=1}^{h} S_i / \sum_{i=1}^{d} S_i \leq 1 - \frac{\alpha}{100} \tag{21}$$

where S_i is the i-th singular value and the total and top numbers of singular values are denoted by d and h, respectively. Therefore, (21) can be simplified as:

$$\sum_{i=1}^{h} S_i / \sum_{i=1}^{d} S_i \geq \frac{\alpha}{100} \tag{22}$$

The top PCs should be selected to accommodate $\alpha\%$ of the actual information of ship performance and navigation parameters. Hence, (6) can be written as:

$$\hat{X}(t) = W_d Y(t) = \underbrace{U_t \Sigma_t}_{=W_d} Y(t) \tag{23}$$

One should note that (23) represents the modified linear function of the data expansion step (i.e. the decoder) of the autoencoder. Hence, (20) and (23) are used as the optimal linear functions for the data compression and expansion steps of the autoencoder and the results are presented in the following section.

3. Data analysis

3.1. Vessel instrumentation

The respective data set of ship performance and navigation parameters is collected from a bulk carrier with following particulars: ship length: 225 (m), beam: 32.29 (m), gross tonnage: 38.889 (tons), deadweight at max draft: 72.562 (tons). The vessel is powered by 2 stroke main engine (ME) with maximum continuous rating (MCR) of 7564 (kW) at the shaft rotational speed of 105 (rpm). Furthermore, the vessel has a fixed

Table 1
Min and Max. Values of ship performance and navigation parameters.

Parameter	Mini.	Max.
1. Avg. draft (m)	0	15
2. STW (Knots)	3	20
3. ME power (kW)	1000	8000
4. Shaft speed (rpm)	20	120
5. ME fuel cons. (Tons/day)	1	40
6. SOG (Knots)	0	20
7. Trim (m)	−2	6
8. Rel. wind speed (m/s)	0	25
9. Rel. wind direction (deg.)	2	360
10. Aux. fuel cons. (Tons/day)	0	8

pitch propeller, diameter 6.20 (m), with 4 blades [26,27] . The data set consists of the following parameters: average (Avg.) draft, speed through water (STW), main engine (ME) power, shaft speed, ME fuel consumption (cons.), speed over ground (SOG), trim, relative (rel.) wind speed and direction (dir.) and auxiliary (aux.) engine fuel consumption (cons.).

Several data pre-processing steps are implemented in this analysis to improve the quality of the ship performance and navigation data set. Firstly, the parameter variations within the selected maximum (max.) and minimum (min.) values are considered and presented in Table 1. The parameter variations beyond the normal operational regions (i.e. beyond max. and min. values) are removed by this step. Secondly, the data set is normalized (i.e. standardization) to equally center and scale parameters, where each parameter is subtracted and divided by the sample mean and standard deviation values of the data set.

3.2. PC calculations

The PCs of the ship performance and navigation data set are calculated and the respective singular values (SV) are presented in the top plot of Fig. 2 in ascending order. Then, each singular value is divided by the sum of singular values and presented in the middle plot of the same figure. That shows the percentage of ship performance and navigation information that each singular vector consists of. The values that are derived in the previous step are subtracted from 1 and presented in the bottom plot of the same figure. This plot shows that the percentage of the actual ship performance and navigation information that can preserve by removing each principal component. The results can be interpreted as: the top 10, 9, 8, 7 and 6 principal components can preserve 100%, 99.92%, 99.48%, 97.86% and 94.03% of the actual ship performance and navigation information. The respective 99% and 95% lines are also presented in the same plot. The top 7 principal components are selected as the benchmark level for this data analysis and that can preserve approximately 97.86% of the ship performance and navigation information. One should note that this step reduces a 10 parameter data set of ship performance and navigation information into a 7 parameter data sets (i.e. compressed data set of 7 new parameters).
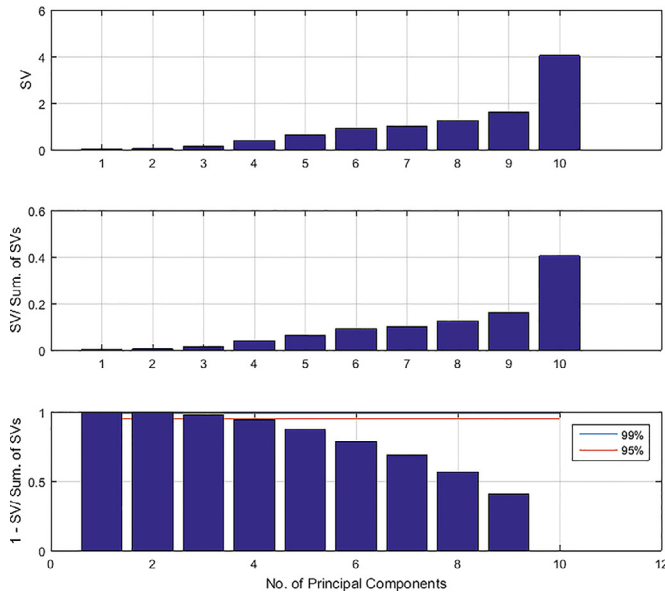
Fig. 2. Autoencoder system architecture.

3.3. Measured and estimated data

The respective histograms for ship performance and navigation parameters are presented in the plots of the first column in Fig. 3. The same parameters are normalized (i.e. standardization) to use under PCA [28–30] as a part of the autoencoder system architecture and the results are presented in the plots of the second column in the same figure. The new parameters are derived by projecting measured ship performance and navigation parameters into the respective PCs and the results are presented in the plots of the third column in the same figure. That are denoted by $X_{P1}(t)$, $X_{P2}(t)$, ..., $X_{P10}(t)$ and a decreasing trend on the variance values of these parameters can also be noted because the singular values are decreasing in the same order. The new parameters derived by considering the top 7 PCs (i.e. the compressed data set) are selected to communicate from the encoder to the decoder of the autoencoder in this study. One should note that these PCs preserve 98% of the ship performance and navigation information in this data set.

The compressed data set is transferred to the decoder of the autoencoder, where the respective data set should be expended to its original parameters. The decoder receives a data set of 7 parameters and that should be transformed into a data set of 10 parameters. The same PCs (i.e. the data structure) are used to expand the compressed data set of ship performance and navigation parameters. The output of the decoder is categorized as estimated ship performance and navigation data set. The respective histograms for each estimated (Est.) ship performance and navigation parameters are presented in the plots of the fourth column of Fig. 3. The histograms for measured ship performance and navigation parameters (Msd.) are also presented in the same plots. One should note that these are the initial ship performance and navigation parameters that are measured by the onboard sensors. Some variations among measured and estimated histograms (i.e. ship performance and navigation parameters) can be observed in these plots. The estimated ship performance and navigation data represent some parameter degradation conditions due to the data compression and expansion steps of the autoencoder.

The measured and estimated ship performance and navigation parameters with respect to the sample number are presented in Fig. 4. The time duration between two consecutive data points is 15 (min). However, some data intervals are not continuous because erroneous data intervals are removed from this data analysis, initially. In general, measured and estimated ship performance and navigation parameters are approximately similar. However, some relatively small parameter variations can also be observed in this figure and that are introduced by the data compression and expansion steps of the autoencoder.

3.4. Data compression ratio

It is noted that estimated ship performance and navigation parameters represent approximately Gaussian type distributions in a majority of the situations due to PCA.

Therefore, the compressed data set can be approximated to 70% of its original size with 98% preserved ship performance and navigation information. This can also be seen as a situation, where 30% of the ship performance and navigation data set is reduced with 2% of information loss. One should note that the information loss may relate to data anomalies and sensor noise, therefore that can negligible in some situations.

The data compression ratio, i.e. the ratio between the uncompressed size and compressed size, is independent of the autoencoder system architecture, but the distribution and redundancy of sensor measurements. If the ship performance and navigation parameters are distributed with low correlations, then the compression ratio may decrease by preserving the same percentage of information. If each parameter is measured by several sensors (i.e. data redundancy), then the compression ratio may increase by preserving the same percentage of information. One should note that such correlations among ship performance and navigation parameters also represent the respective data structure. The respective PCs represent the structure of the ship performance and navigation data set, therefore a proper structure improves the data compression ratio. However, data anomalies and sensor noise conditions can degrade the compression ratio in some situations. In general, ship performance and navigation parameters are often related to each other (i.e. speed-power conditions, trim-draft conditions), therefore a good compression ratio has been observed in this study. Furthermore, the compression ratio can further be increased by introducing multiple sensors to monitor the most important ship performance and navigation parameters and that may relate to the respective application. The data compression ratio may increase in such situations, however the number of ship performance and navigation parameters in the data sets may also increase.
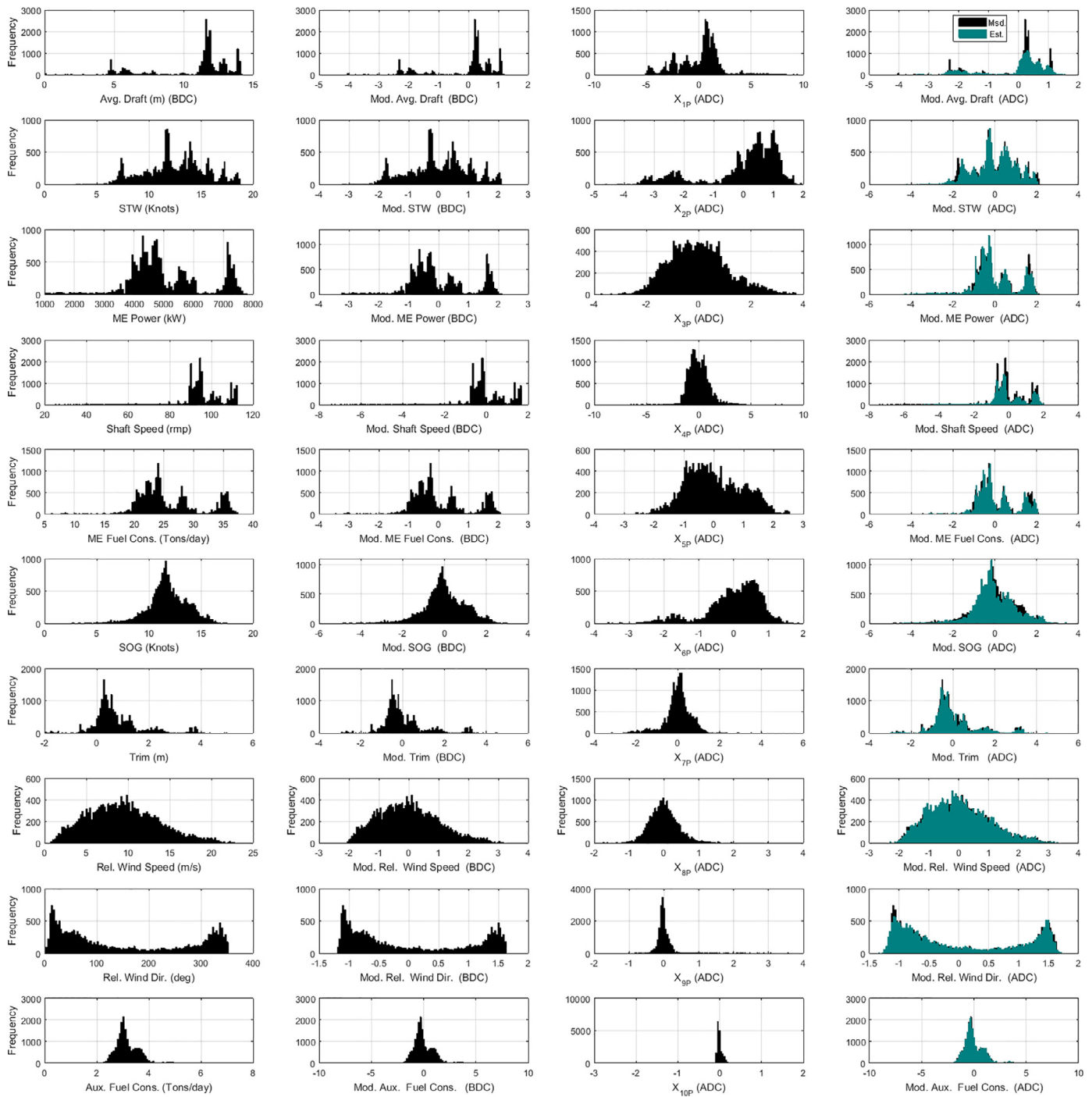
Fig. 3. PCA of ship performance and navigation parameters.

Furthermore, measured ship performance and navigation parameters that have approximately Gaussian type distributions have low information loss in comparison to the parameters with Non-Gaussian type distributions. If the parameters consists Gaussian type distributions, then each PC is an asymptotically consistent unbiased estimate for the respective data set [31]. Therefore, the parameters with Non-Gaussian type distributions in such data sets should be transferred into Gaussian type distributions in possible situations to improve the data compression ratio. It is also noted that the autoencoder transforms ship performance and navigation parameters into approximately Gaussian type distributions, when those parameters are not parallel to any PC. If the PCs are not parallel to the respective parameters, then the same parameters consists of a stronger correlation. Therefore, a negligible data compression ratio (i.e. equal measured and estimated parameter values) can be observed under the autoencoder, i.e. the parameters are parallel to PCs.
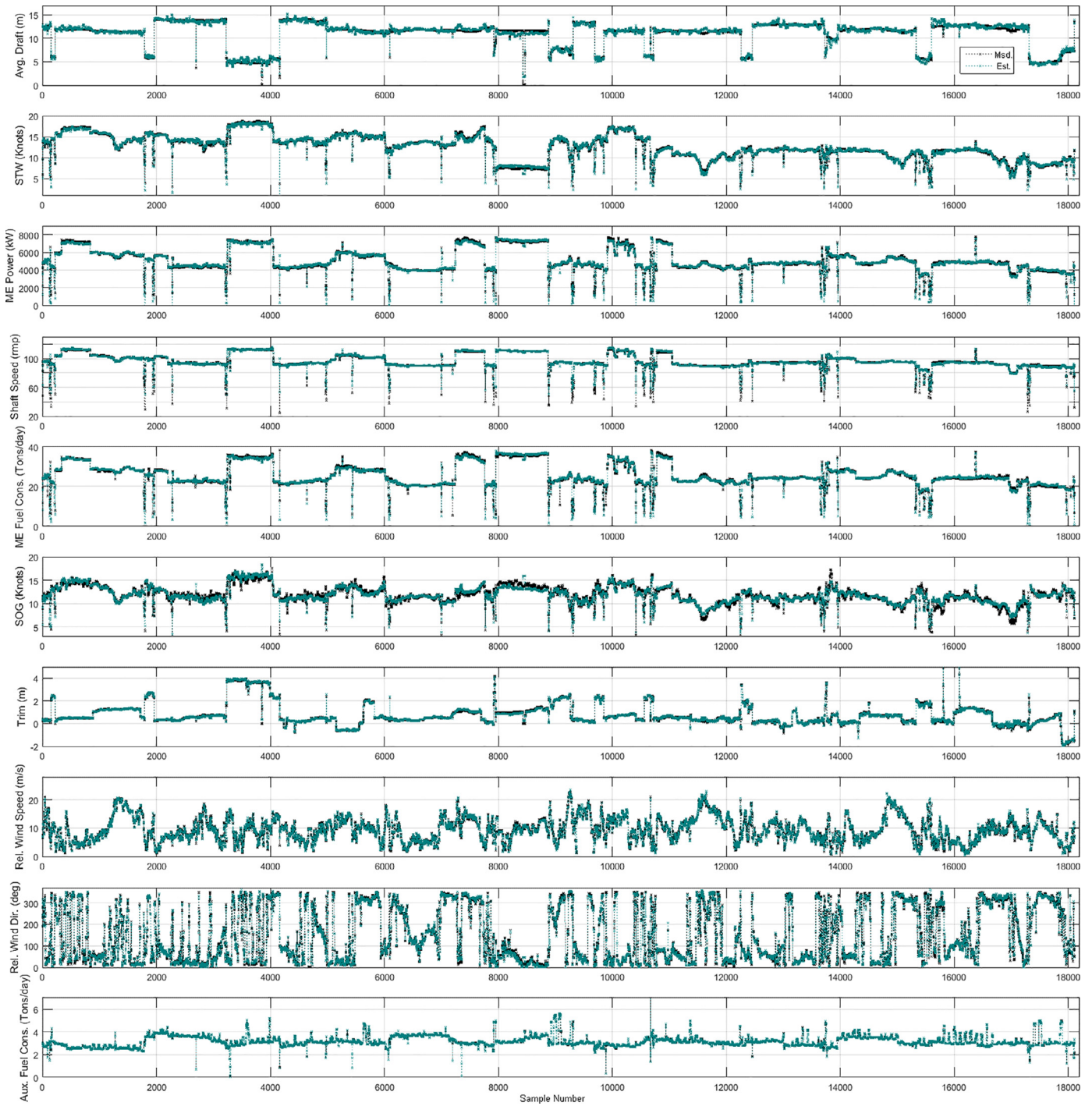
Fig. 4. Measured and estimated parameters of ship performance and navigation data.

The central limit theorem states that, given certain conditions, any independent random variable can be approximated to a Gaussian distribution with well-defined mean and variance values, regardless of the actual distribution of the respective parameter [32]. The autoencoder also approximates the variance of each ship performance and navigation parameter into an approximate Gaussian distribution, where the respective information can retain within the respective PC. It is also recommended that each ship performance and navigation parameter should be transformed into approximately Gaussian type distributions, therefore the data compression ratio can be increased. e.g. rel. wind direction sensor measurements may not consist of a Gaussian type distribution (see Fig. 3). That can be transformed to a Gaussian type distribution by considering an appropriate angle transformation. Therefore, this can be an iterative process, where the amount of information loss vs the parameter compression ratio should be compared to evaluate the autoencoder performance. The outcome of this

study shows that 98% of the variance is retained with the respective 7 PCs. Therefore, only 2% of ship performance and navigation information has lost during these data compression and expansion steps of the autoencoder.

3.5. Improvements in data compression

There are various septs that can be taken to improve the quality of the data compression and expansion steps of the autoencoder. As discussed before, that can be done by transforming the respective parameters into Gaussian type distributions and selecting a minimal number of PCs that can preserve required ship performance and navigation information. Ship performance and navigation parameters can be rearranged to create Gaussian type distributions in some situations. However, ship performance and navigation parameters may not visualize Gaussian type distributions in those situations. Various data clustering approaches in a high dimensional space should be considered to identify appropriate Gaussian type distributions these situations [30]. E.g. marine engines of ocean going vessels may have several operational points, therefor ship performance and navigation parameters can be clustered around Gaussian type distributions under these operational points, in which should be identified by additional algorithms. This approach shows that ship performance and navigation parameters may consist of a combination of several approximately Gaussian type distributions and that should be identified before PCA. Ship performance and navigation data sets should be separated into such Gaussian type distributions and each distribution (i.e. data cluster) should send separately through the autoencoder to improve the compression ratio in those situations [2].

Those data clusters can be compressed and expanded by the autoencoder with approximately similar measured and estimated data sets. One should note that the compression ratio can be higher with lower information loss in such situations. Some ship performance and navigation parameters are more important than others, therefore addition sensors can be introduced to monitor those parameters. That step can strengthen the most important ship performance and navigation parameters within the respective data sets and PCA can identify such situations, i.e. redundant parameter measurements. However, data anomalies, i.e. sensor and DAQ faults and system abnormal events, can degrade the data compression ratio of the autoencoder. Such data anomalies can often be outliers of PCs and that can be detected by using adequate outlier detection filters with the bottom PCs [33]. Since the PCs represent the respective data structure of ship performance and navigation parameters, that can also be used to recover some data anomalies. Therefore, such data anomaly detection and recovery filters can also be a part of the autoencoders, i.e. self-cleaning autoencoders, and that will further improve the quality of the respective data sets. However, additional hardware erroneous conditions (i.e. channel errors and fading) can be introduced into ship performance and navigation parameters during data commination processes. It is believed that such conditions can also be identified, isolated and recov-

ered by a self-cleaning autoencoder system architecture [34]. However, such additional features will be integrated into the proposed autoencoder system architecture in the future work of this study.

One should note that self-cleaning autoencoders can be an important part of onboard data handling processes of modern vessels. When vessels are equipped be such large number of onboard sensors, these steps discussed in this section can make a considerable contribution to improve the respective data handling processes. Furthermore, autoencoders with a good compression ratio can help the data handling processes to reduce the required computational power in onboard vessels.

4. Conclusion

Ship owners often use the average values of ship performance and navigation parameters and that reduce the size and cost of transferring, handling and analyzing the respective data sets. The main objective in this study is to show that ship performance and navigation data sets can be reduced in their sizes by the autoencoder system architecture, while having a high sampling rate. Therefore, the respective ship performance and navigation parameters can be stored and analyzed with a high data sampling rate in such situations. The will further improve the information visibility of vessel operational and navigation conditions.

An autoencoder system architecture compresses and expands data sets of ship performance and navigation parameters, which should be transferred through communication networks as reduced data sets but with a considerable amount of information. The encoder and decoder should develop as software functions, therefore the autoencoder system architecture may not depend, extensively on the hardware systems of modern vessels. In general, the encoder should be implemented in onboard vessels and the decoder should be implemented in onshore data centers. The data transmission process also plays an important role under the autoencoder system architecture. In general, some vessels transmit ship performance and navigation data under satellite communications to data centers, while the respective bandwidth is free. Other vessels transmit ship performance and navigation data under wireless communication to data centers, while the vessels are within port areas. Therefore, the respective data centers can locate within the port areas with the required infrastructures, where the proposed autoencoder system architecture can be implemented.

Autoencoders derive a new reduced set of parameters that is another representation of measured ship performance and navigation parameters. These new parameters consist of a considerable amount of ship performance and navigation information, therefore the capabilities of using those parameters to quantify ship performance and navigation conditions instead of using measured parameters should be further investigated. Hence, optimal vessel operational and navigation situations can be identified to archive the respective energy

efficiency requirements in shipping by considering the autoencoder system architecture.

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