Machine Intelligence based Data Handling Framework for Ship Energy Efficiency

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***Abstract*— Appropriate navigation strategies should be developed to overcome the current shipping industrial challenges under emission control based energy efficiency measures. Effective navigation strategies should be based on accurate ship performance and navigation information, therefore various onboard data handling systems are installed on ships to collect large-scale data sets. Ship performance and navigation data that are collected to develop such navigation strategies can be an integrated part of the ship energy efficiency management plan (SEEMP). Hence, the SEEMP with various navigation strategies can play an important part of e-navigation under modern integrated bridge systems. This study proposes a machine intelligence (MI) based data handling framework for ship performance and navigation data to improve the quality of the respective navigation strategies. The prosed framework is divided into two main sections of pre and post processing. The data pre-processing is an onboard application that consists of sensor faults detection, data classification and data compression steps. The data post processing is a shore-based application (i.e. in data centers) and that consists of data expansion, integrity verification and data regression steps. Finally, a ship performance and navigation data set of a selected vessel is analyzed through the proposed framework and successful results are presented in this study.**

***Index Terms*— Shipping industry, big data, data handling, energy efficiency, emission control, machine intelligence.**

I. Introduction

A. Navigation Strategies

A global vision for an international collaborative communication network to improve the safety and efficiency considerations in shipping is proposed under "e-navigation" [1]. It is expected that this framework also facilitates towards standardized ship navigation platforms, including integrated bridge systems (IBSs), to overcome the present energy efficiency and emission control challenges. Appropriate navigation strategies under IBSs should be developed to overcome such challenges especially under emission control areas (ECAs) as a part of the e-navigation framework. One should note that e-navigation is classified as a user driven concept rather than a system driven concept at the present stage. However, modern ship navigation platforms with intelligent decision support capabilities [2], where some limitations on human subjective factors are enforced, are also considered under the same [3]. It is expected that these intelligent decision support capabilities eventually influence on various ship navigation strategies as a part of e-Navigation. Those facilities not only enhance the navigation safety but also improve the operational efficiency in shipping [4]. Ship Navigation strategies are often developed under safety and efficiency considerations. A number of studies are conducted on the safety related ship navigation strategies, especially under rough weather conditions ([5], and [6]). Even though the concept of energy efficient ships is highlighted in the recent years, the operational efficiency related navigation strategies are relatively novel concepts for the shipping industry.

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B. Energy Efficient Ships

The International Maritime Organization (IMO) and other respective maritime authorities introduced various emission control (i.e. CO2, SOx, and NOx) regulations to improve energy efficiency in shipping. Furthermore, tighter emission control measures for vessels are introduced in designated emission control areas (ECAs) by the respective maritime authorities [7]. These emission control regulations inforce to implement various energy efficiency measures under the Ship Energy Efficiency Management Plan (SEEMP). Hence, the SEEMP can facilitate to develop appropriate navigation strategies to accommodate such emission control based energy efficiency measures as a part of modern IBSs. Adequate ship performance and navigation data should be collected under IBSs to develop such ship navigation strategies. Furthermore, effective navigation strategies are based on the quality of ship performance and navigation information that are extracted from the data sets. One should note that the data handling processes often influence on the quality of ship performance and navigation data. Modern IBSs are facilitated by the required sensors and data acquisition systems (DAQs) to support such data handling processes.

C. Integrated Bridge Systems

Modern IBSs consist of two separate networks of navigation and automation systems to satisfy various classification societies' requirements. This separate network architecture further improves the reliability and safety considerations of ship navigation. In general, navigation systems consist of radar, conning, electronic chart display and information system (ECDIS), autopilot system and other related sensors. Hence, a comprehensive overview of ship navigation conditions can be observed. In general, the automation systems consist of a power management architecture for engine and propulsion control systems with respect to various engine room operations. Additional units of bilge and ballast control, HVAC and alarm & monitoring systems can also be a part of these automation systems. Hence, a comprehensive overview of ship performance conditions can be also observed.

Both systems facilitate to obtain ship performance and navigation data and that data should be visualized. appropriately. Such data visualization methods can be used to observe optimal ship performance and navigation conditions. Optimal performance and navigation conditions can be compared with the vessel current conditions in IBSs to develop decision support facilities. That process may identify energy efficient operational conditions of vessels under the SEEMP through ship performance and navigation data. Those facilities eventually develop the respective navigation strategies of ship energy efficiency. However, the same ship performance and navigation information creates large-scale data sources and introduces additional data handling challenges in IBSs.

II. Performance & Navigation Data

A. Data Handling

These data handling issues can be categorized as internal and external challenges in shipping. The internal challenges relate to the data quality and quantity. Large scale data sets of ship performance and navigation information collected by the respective sensors and data acquisition systems create both quality and quantity issues. The quantity issues are often addressed under data management applications. The data quality issues are the focus of this study and that should be addressed under real-time data handling platforms of IBSs. The external challenges mainly relate to data communication and storage issues, where the cost effectiveness of handling large data sets should be considered. One should note that the data quantity issues influence as an external challenge in data handling process in some situations. Therefore, possible solutions to such situations should be considered under the same data handling framework. However, both internal and external challenges in handling large-scale data sets are often categorized as "big data challenges" [8-9] in the recent literature.

B. Recent Studies

Similar industrial challenges encountered in handling ship performance and navigation data (i.e. collected under onboard sensors and data acquisition systems) are presented under various data analyses. Data analysis of operational energy efficiency in an inland river ship is presented in [11]. A performance evaluation approach for a steam-propelled merchant ship is presented by collecting the respective data in [12]. Several data analyses on fuel usage for ship operations are presented by [13-15]. Statistical analysis performed on data collected from sea trials of a small training ship is presented in [16]. Full-scale data analysis for a passenger ferry to evaluate vessel performance is presented in [17]. Furthermore, additional studies are integrated with port performance evaluation systems in [18]. However, these studies ignore the internal and external challenges that are associated with the respective data sets. If such challenges in the data handling process have not been resolved, properly, that can degrade the information extracted from ship performance and navigation data. Hence, an appropriate onboard data-handling framework with various data analytics to overcome such data handling challenges in shipping is proposed as the main contribution of this study. Even though there are several data handling approaches suggested for shipping industrial applications [19], a proper guide with the required steps in both onboard and onshore has not been presented. Therefore, such approaches have often been considered as trial and error procedures. The proposed data handling framework consists of a proper guide with the required steps (i.e. data analytics) to overcome data handling challenges in shipping. Even though similar data analytics has been presented in the recent literature, it has not been presented in a proper structure to implement as both onboard and onshore applications.

C. Data Analytics

An improved data handling framework can make appropriate navigation strategies towards energy efficient ships [10]. The proposed framework consists of several steps (i.e. data analytics) to handle large scale data sets in real-time and develop more cost-effective solutions in shipping. Such data analytics can be used under IBSs and data centers to overcome the respective data handling challenges in shipping. Data analytics consist of an analysis methodology that observes hidden data patterns, clusters, correlations and other useful information of the respective data sets. Even though a majority of data analysis methods are based on various empirical ship performance and navigation models [20], these conventional mathematical models often fail to handle large-scale data sets due to system-model uncertainties, sensor noise and fault conditions and complex parameter interactions. Hence, such models may not adapt and predict actual ship performance and navigation information and that can influence the validity of ship navigation strategies.

Machine intelligence (MI) based data analytics are proposed in this study to overcome such model related challenges. One should note that such MI applications are often associated with statistical analysis techniques and that are often implemented by other transportation systems with various sensors, data acquisition and communication networks to overcome the similar challenges. Furthermore, superior data analytics are demanded by modern transportation systems to preserve the required navigation safety and efficiency levels in the recent years. Similarly, this combination (i.e. statistical data analyses and MI techniques) can address various fundamental handling challenges in large-scale data sets in shipping. The improved data sets lead towards better ship navigation strategies with energy efficient operating conditions.

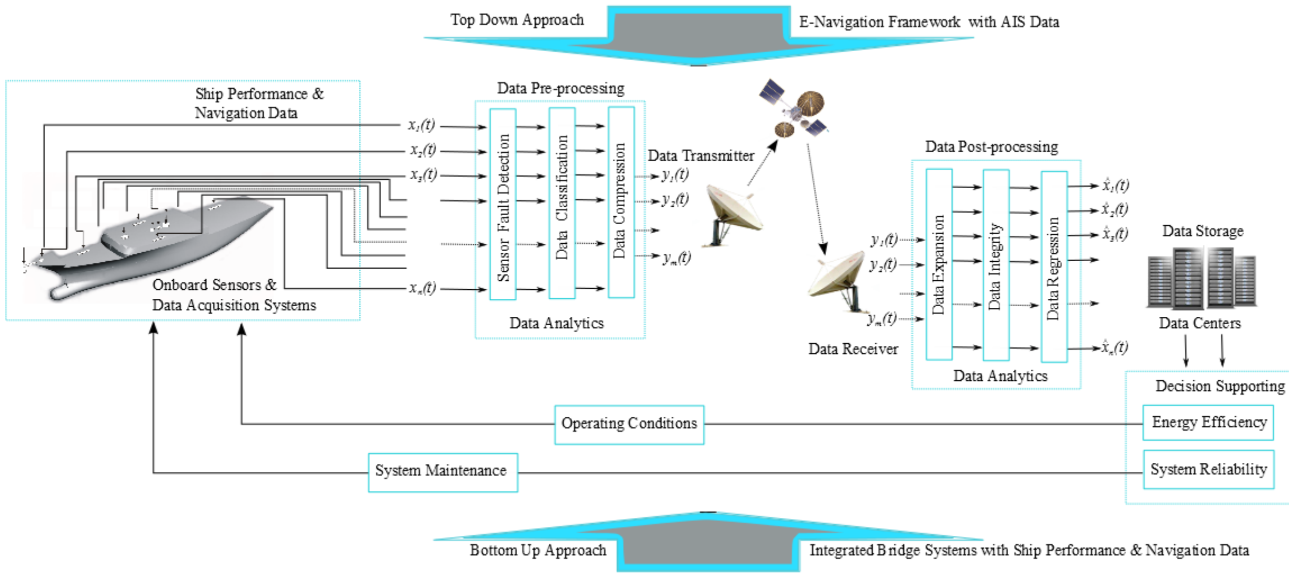

Figure 1. Data handling framework

III. Machine Intelligence

A. Data Handling Framework

The proposed data handling framework with ship performance and navigation data is presented in Figure 1. This framework is supported by both top down and bottom up approaches. The top down approach is facilitated by e-navigation environment with AIS data. e-navigation framework enables the transfer of ship performance and navigation data among ships and shore based centers, where the respective decision and action information of vessels can be extracted. That further enhances the proposed data handling framework by delivering timely, reliable, and accurate information of vessels. The bottom up approach is facilitated by integrated bridge systems with onboard sensors and data acquisition systems. Hence, ship performance and navigation data collected by both top down and bottom approaches support the proposed data handling framework. That consists of various MI application layers (i.e. data analytics) to overcome the respective data handling challenges. Each step of the data handling framework, appropriate MI applications are introduced as further described in Figure 1.

Firstly, ship performance and navigation data are collected from various onboard sensors and data acquisition systems in the vessel. Then, these sensor data (i.e. the ship performance and navigation parameters) are transferred through a data pre-process. The pre-processed data are communicated through data transmitters (i.e. onboard the vessel) in much smaller improved data sets. The pre-process is further divided into three sections: sensor fault detection, data classification and data compression. The same data sets are obtained by shore based data centers through data receivers. Then, these data sets are handled through a data post-process and accommodated in data storage facilities as required. The post-process is further divided into three sections: data expansion, data integrity, and data regression.

The pre-post processed data are used for various decision supporting features especially under energy efficiency and system reliability applications of shipping. The energy efficiency applications consist of identifying optimal vessel operating conditions to reduce overall fuel consumption. The system reliability applications consist of identifying the health conditions of onboard systems and that information can be used to develop optimal maintenance actions to reduce the system operating costs. However, both applications should be supported by appropriate visualization methods.

B. Data Visualization

The speed-power plot with respect to relative wind conditions of a selected vessel is visualized in Figure 2. The vessel is 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). That is powered by 2 stroke main engine (ME) with maximum continuous rating (MCR) of 7564 (kW) at the shaft rotational speed of 105 (rpm). It has a fixed pitch propeller diameter of 6.20 (m) with 4 blades [21]. The respective speed power data set is standardized in the figure, where the mean values are subtracted from each parameter and the variance values set to be 1.0 (i.e. each parameter with an equal variance). This approach (i.e. data scaling) is taken as a part of principal component analysis (PCA) to avoid the situations such as: the parameters with large variance values make bigger contributions on the data analysis. Therefore, each parameter can have a same variance and influence equally in this data analysis. Furthermore, following observations are also noted with respect to the same speed-power plot. The vessel is losing its speeds due to high relative wind conditions for the same engine power levels. High wind conditions create rough sea conditions, therefore ship resistance increases, and ship speed decreases. Low speed maneuvering situations of the vessel are removed from this data set to improve the visibility of ship performance and navigation information [22]. Hence, such data visualization methods can play an important role in a data handling

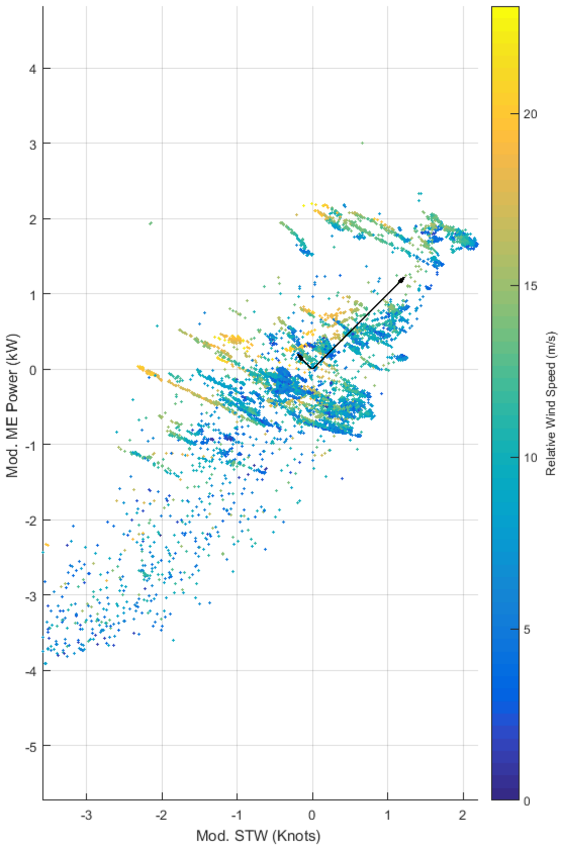

Fig. 2. Mod. Speed Power Plot with PCA framework.

C. *Sensor Fault Detection*

The first step in data pre-processing is sensor fault detection. Detecting sensor fault situations and removing those erroneous data regions from the ship performance and navigation data are considered in this step. Firstly, this study proposes to identify these sensor fault situations by observing the mean and variance values of each parameter. Each parameter in the ship performance and navigation data set may have a range, where the parameter can vary e.g. ship speed varies from 0 (Knots) to 20 (Knots) in the selected vessel. Therefore, if the ship speed is going beyond this range that situation categories as a sensor fault situation. Secondly, other sensor fault situations are identified by the covariance values among the respective parameters. e.g. a clear relationship among ship speed, power and wind speed can be observed in Figure 2 under the respective principal components (PCs).

PCA is a non-parametric method for extracting relevant information from various data sets. A new basis for the respective data set is derived from the original basis (i.e. the respective parameters) with a linear combination of the original basis. This new basis is the respective principal components of the ship speed power data set and presented as two vectors in Figure 2. That PCA structure represents the largest independent covariance directions of the same data set. These two vectors represent an approximately linear relationship between the speed power values of the vessel. The lengths of these two vectors relate to the covariance values of the vessel speed power parameters. Therefore, such linear

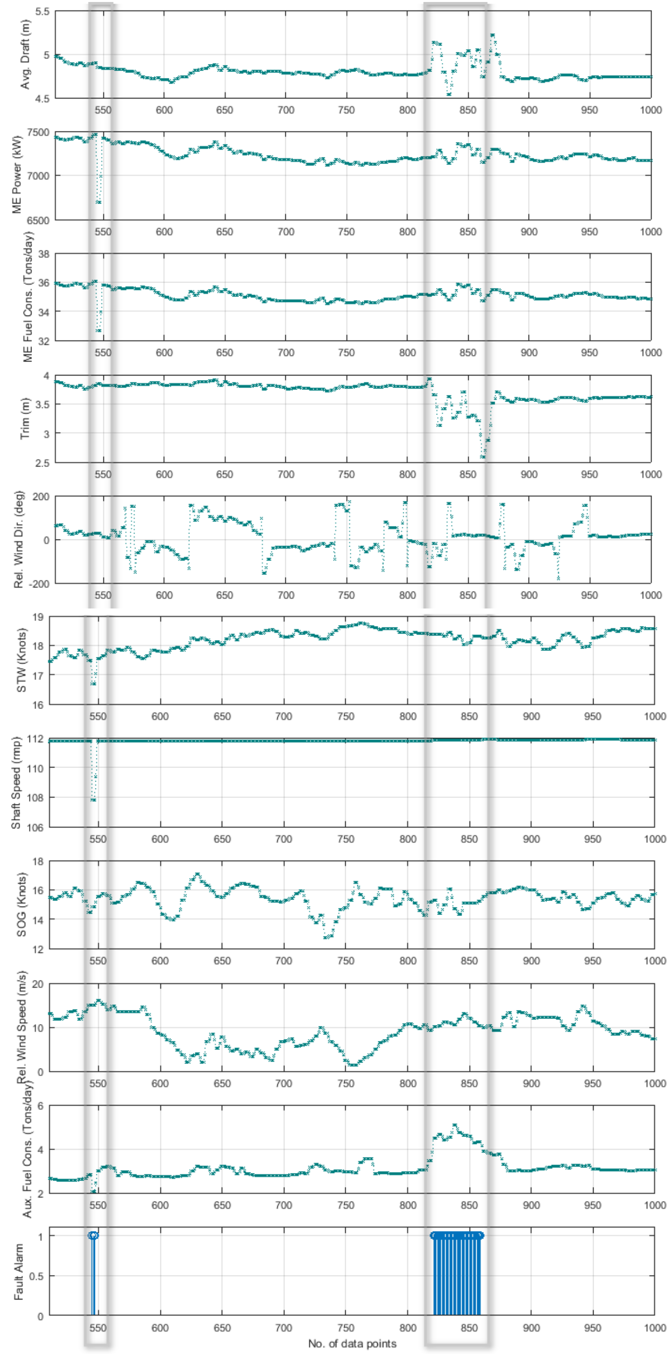

Fig. 3. Ship performance and navigation parameters with sensor faults.

relationships among ship performance and navigation parameters can be used to identify sensor fault situations. e.g. any data point that represents a contradictory relationship between these speed and power principle components can be categorized as a sensor fault situation (see Figure 2).

The same covariance values (i.e. PCs) can be developed for a high dimensional data set and that represent complex interactions among ship performance and navigation parameters [23]. Such information (i.e. the PC structure) can extensively be used to identify various sensor fault situations by observing unusual parameter behavior. One should note that that some erroneous data conditions are related to DAQs failures that are also recorded as sensor faults. However, both

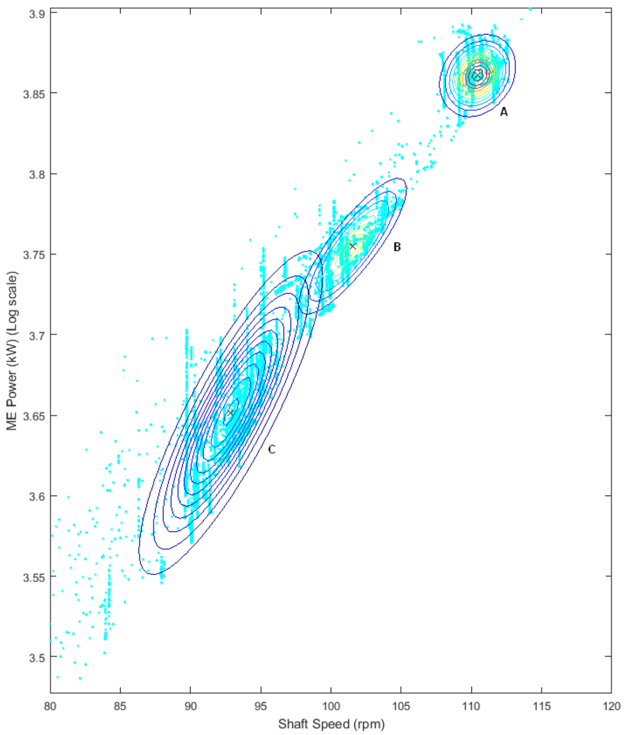

Fig. 4. Engine Propeller Combinator Diagram with GMMs and EM algorithm

fault types can be identified by the proposed approach. The proposed framework is implemented on a 10 dimensional data set of ship performance and navigation parameters and the results are presented in Figure 3. The respective parameters (i.e. 10 parameters) are presented in the top 10 plots and the detected faults situations (i.e. fault alarm) are presented in the bottom plot. One should note that these plots are presented with respect to the number (No.) of data points (i.e. sample number) and the time interval between two consecutive data points is 15 (min). Two sensor faults situations are detected in this data set and denoted by two windows.

In the first sensor fault situation, several parameters (main engine (ME) power, ME fuel consumption, STW, shaft speed, and auxiliary engine fuel consumption) are associated with some unusual behavior (i.e. a sudden drop in the parameter value). In the second sensor fault situation (i.e. a data interval), several parameters (i.e. average draft, trim) are associated with unusual behavior and the auxiliary engine fuel consumption has increased, considerably. Therefore, such situations are detected as sensor fault situations. Various relationships among ship performance and navigation parameters should be investigated under the PCA (i.e. a higher dimensional space) and that knowledge can used to identify complex sensor fault situations [24] as presented in this study.

D. Data Classification

Data classification of ship performance and navigation information is considered as the next step of this framework. A marine engine centered data classification approach as the basis to develop the respective navigation strategies is considered. Therefore, the large scale data sets are classified into several sub-sets with respect to engine operating regions of the vessel. Other parameters in ship performance and navigation data are also divided along the same classification borders. Ship performance and navigation data can be visualized appropriately by this method as small data sets. The results of the proposed data classification approach are presented in Figure 4. The figure represents an engine propeller combinator diagram, where main engine power (in log scale) and shaft speed (rpm) values are presented. The most frequent engine operating regions are identified as A, B, and C by Gaussian mixture models (GMMs) with an expectation maximization (EM) algorithm. The GMM approach is implemented to cluster the respective ship performance and navigation data and the information is also used to identify the respective operating regions in the main engine. Furthermore, the EM algorithm is implemented to calculate the respective parameters of the GMMs [25]. One should note that GMMs are denoted as multivariate Gaussian distributions with the respective mean and covariance values. Therefore, the respective contours of the multivariate Gaussian distributions are denoted by ellipse in the same figure.

E. Data Compression and Expansion

The last step in data pre-processing is the data compression step and the first step in data post-processing is the data expansion step. One should note that the dimensionality of the classified ship performance and navigation data set is reduced [26] by the data compression step. Data region A classified under the previous step (see Figure 4) is considered for these compression and expansion steps. The respective parameters in ship navigation and performance data (i.e. average (avg.) draft, speed through water (STW), ME power, engine shaft speed, ME fuel consumption, speed over ground (SOG), trim, relative wind speed and wind direction) are also classified along the same engine operating regions.

An autoencoder network is proposed for these two steps (i.e. data compression and expansion) [27]. Autoencoder is an unsupervised learning method with a feed-forward neural network, which is also categorized as a deep learning approach [28-31]. The main objective of designing an autoencoder is to recreate the same input at the output of the neural network. A hidden layer that compresses/expands the respective data set is located between the input and output layers of an autoencoder. The input data set is compressed and transmitted by the first hidden layer of the autoencoder. Hence, the new data set consists of a linear combination of the measured parameters of ship performance and navigation information. The comparison accuracy between the input and output data sets is used to evaluate the success of the network.

The number of parameters in this new data set is adjusted in accordance with the hidden layer of the autoencoder. Therefore, the number of nodes in the hidden layer should select appropriately, where the important variance values in the data set are preserved. The same PCA structure that is developed in the previous step can be used as the data compression and expansion functions in the autoencoder. The compressed data sets are transmitted through a satellite network to data centers for data storage and further analyses.

The compressed data set is received and expanded by the second hidden layer of the autoencoder. The input to the encoder is the previously classified data set (i.e. data region A) in this situation. The output of the autoencoder is the estimated ship performance and navigation parameters. The respective data compression and expansion results are presented in Figures 5 and 6. The actual and estimated ship performance and navigation parameters have some variations (i.e. data errors) and the autoencoder performance is evaluated with respect to those data variations.

The input and output data sets of an autoencoder as statistical distributions are presented in Figures 5 and 6. The first column from the left represents the statistical distributions of actual ship performance and navigation parameters. The second column from the left represents the same standardized parameters, which are the inputs to the autoencoder. The third column from the left represents the compressed data set, i.e. the projected data set along the respective principle components (PCs), and that is transferred through communication networks. Even though the all new parameters are presented in this situation, these parameters that relate to the top PCs should be selected, appropriately to transfer through communication networks. The forth column from the left of the figure represents the parameters (i.e. estimated parameters) of the expanded data set, which is the output of the autoencoder. One should note that the compressed data set along with PCA information should be transmitted to data center to expand the data set into its original format. Even though the pre and post-processing steps may have the data sets with the same sizes, that may not be a mandatory requirement for this data handling framework. However, that information can be used to evaluate the autoencoder performance.

Finally, the respective input and output parameters of ship performance and navigation data are compared to evaluate the autoencoder performance. Considering the second (i.e. the inputs) and forth (i.e. the outputs) columns of Figure 5, the following conclusions are derived. The input and output statistical distributions of the respective parameters are approximately similar in a number of situations. However, some parameters may not recover, completely due the data compression and expansion steps of the autoencoder. A data set with 9 ship performance and navigation parameters is considered and compressed by the autoencoder (i.e. the top 7 PCs) and the compressed data set consists of 99.5 % of actual ship performance and navigation information. The data compression ratio in this situation is 22% (i.e. 7/9 parameters) and that preserves 99.5% of the respective ship performance and navigation information. One should note that the respective information percentage (i.e. 99.5%) relates to the top PCs [27]. Therefore, the top PCs should be selected, appropriately to preserve the useful information in ship performance and navigation data as a necessary step for the data compression. The actual and estimated parameters of ship performance and navigation information with respect to the number (No.) of data points are presented in Figure 6. These data points are not presented in a continuous time line, because some erroneous data intervals are removed from this data analysis, initially.

F. Data Integrity Verification

The next step of data post-processing is integrity verification. A sub-set of ship performance and navigation data is always transferred by ships as automatic identification system (AIS)

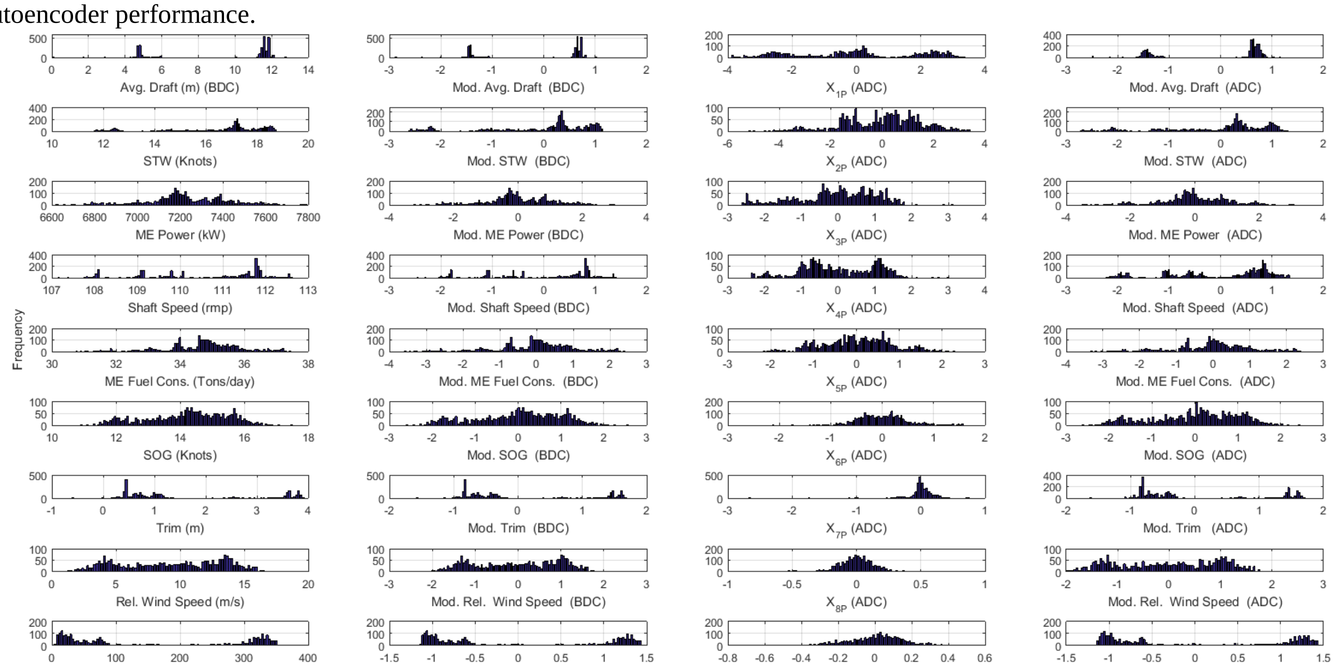

Fig. 5. The input and output data sets of an autoencoder as statistical distributions.

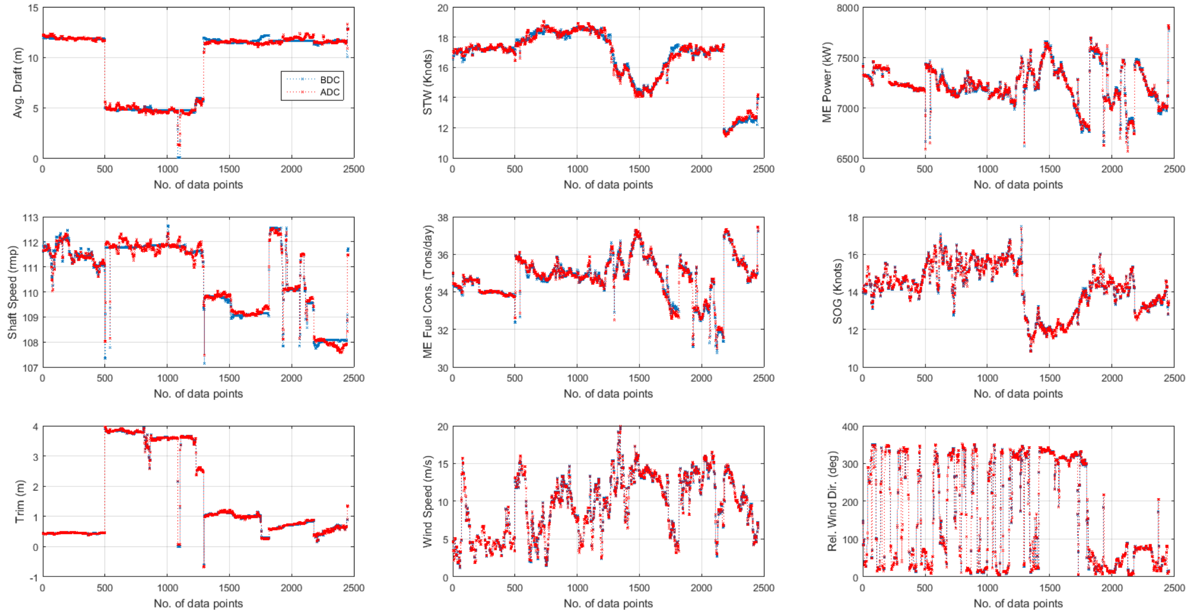

Fig. 6. The input and output data sets of an autoencoder as No. of data points

messages. AIS messages have often been used by vessel traffic services (VTS) and other maritime authorities for identifying and locating vessels. Similarly, that information is also exchanged electronically through other ships, AIS base stations, and satellites nearby. This information is also possible to obtain by shore based data centers to improve the integrity of ship performance and navigation data that are collected by the onboard systems. Furthermore, additional data sources (i.e. recorded weather data) can also be used to improve the data integrity. One should note that any erroneous data regions that are introduced by the communication networks can be identified by this step at shore based data centers.

G. *Data Regression*

The last step of this data handling framework is data regression. The estimated data points of ship performance and navigation information are used to calculate the actual parameter values of ship performance and navigation data. This step may consist of various smoothing algorithms to reduce the fluctuations of the estimated data points. Furthermore, this step can improve the information visibility among the respective parameters and facilitate to understand optimal ship performance and navigation conditions. That information can also be used to evaluate ship energy efficiency under various navigation and operational conditions.

IV. Conclusion

The main objective of this study is to develop an appropriate onboard data-handling framework with various data analytics to overcome current data handling challenges in shipping. The proposed data handling framework consists of two main sections of pre and post processing. The data pre-processing section is an onboard application and that consists of sensor faults detection, data classification and data compression steps. The pre-process can improve the quality and reduce the quantity of ship performance and navigation data. Hence, the pre-process can reduce the computational burden on the onboard crew, where improved and reduced data sets can be delivered the shore based data centers. The data post processing section is a shore based application (i.e. in data centers) and that consists of data expansion, integrity verification and data regression steps. The post-process can further improve the quality and visualize the information of the same. The post-process can reduce the complexities on handling large-scale data sets, where high skilled crew to analyze such data sets should not always be presented in data centers.

Various MI applications such as PCA, GMMs with an EM algorithm and autoencoders are proposed and implemented in various sections of the data handling framework. One should note that such MI techniques can introduce special features of self-learning (i.e. data clusters and PCs), self-cleaning (i.e. sensor fault detection, data regression & integrity verification), self-compression & expansion (i.e. data compression and expansion) into the respective data sets under the proposed data handling framework. Even though various MI techniques are presented in the literature, this study presents an appropriate structure to implement those techniques and improve information visualization.

The improved data visualization can be used to identify optimal ship performance and navigation conditions from the respective data. Those conditions can be used to develop appropriate navigation strategies for energy efficiency operational conditions of ships under the SEEMP. Hence, the proposed framework can handle such large-scale data sets as a big data solution and improve the outcome of the respective navigation strategies. These energy efficient navigation strategies [32] with intelligent decision support capabilities [33] can eventually be a part of the e-navigation strategy at the global level and the SEEMP [34] at the local level (i.e. in the vessel).

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