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The development of a ship-server power / emission assessment model: case study on big data analysis for real-time ship operation

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THE DEVELOPMENT OF A SHIP-SERVER POWER / EMISSIONS ASSESSMENT MODEL: CASE STUDY ON BIG DATA ANALYSIS FOR REAL-TIME SHIP OPERATIONS

By

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A dissertation submitted to the World Maritime University in partial fulfilment of the requirement for the award of the degree of

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DECLARATION

I certify that all the material in this dissertation that is not my own work has been identified, and that no material is included for which a degree has previously been conferred on me.

The contents of this dissertation reflect my own personal views, and are not necessarily endorsed by the University.

(Signature): ....

(Date): **24th September 2019**

Supervised by: **Professor Dr. Aykut I. Ölçer**

World Maritime University

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ABSTRACT

Title of Dissertation: ***The development of a ship-server power / emissions assessment model: case study on big data analysis for real-time ship operations***

Degree: **Master of Science**

Disruptive technology, which is gradually enveloping the maritime industry with promises of improving ship operations and safety, certainly has some drawbacks. Some of the challenges identified are cyber security, data ownership, secret data theft, and processing framework.

Recently, with the advent of Shipping 4.0, several technological changes have been witnessed to improve ship operations, such as the kiber helmet used to support engineers offshore, drones used for CO_2 emissions monitoring, the "Electric Blue", a future ship concept by Roll-Royce, Cargo visibility used by Maersk, UK's Martek Marine, Class Nk and NAPA's fleet intelligence and so on.

The technologies have one thing in common, the use of data. Recent ship design solutions come with several thousands of sensors, CPS and IoT to improve ship operation. However, aside the identified challenges, there is no literature, to the best knowledge of the author, that quantifies the emissions caused by the use of these telemetry devices and services.

This research identifies sources of ship big data, its transmission, processing and storage. It also incorporates the land based energy calculation for determining the power consumed by servers, which houses applications that processes ship big data. This is done using an emission calculator tool developed with Netbeans IDE 8.0.2 and java programming language, and the creation of two model scenarios.

To complete this investigation, ship engine related data from the EU funded TEFLES research project was used. Data acquired from the project was pre-processed using statistical tools. The idea was to compare the energy consumption and emissions of a ship in the three (3) operating modes, sea, manoeuvring and at port.

In this thesis various factors that affect the server CPU utilization are identified. Some are the PUE of a data center, the CPU utilization rate, and the carbon factor. For this investigation, the most significant factor identified was the CPU utilization and the grid carbon factor.

The results, however, reveal that about 1.75% of additional CO_2 is emitted by 20 ships on the Baltic sea route for a distance of 530 miles. However, the relationship between the additional emissions created with the use of real-time application and the ship is not linear; the additional emission depends on the amount of time real-time applications for ship operations are accessed.

To limit further increase, several measures such as subscribing for SaaS and sector ownership of datacenter may be recommended as full ship autonomy approaches.

KEYWORDS: 4IR, Shipping 4.0, IoT, SaaS, CPU, PUE, Energy consumption of servers, Emissions calculation modelling

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LIST OF ABBREVIATIONS

4IR	Fourth Industrial Revolution
AI	Artificial Intelligence
AIS	Automatic Identification System
CoC	Confirmation of Compliance
CPS	Cyber Physical System
CPU	Central Processing Unit
DBMS	Database management system
DCP	Data Collection Plan
DCS	Data Collection System
EEDI	Energy Efficiency Design Index
EEOI	Energy Efficiency Operational Indicator
EnMS	Energy Management System
GHG	Greenhouse gas
GISIS	Global Integrated Shipping Information System
IEA	International Energy Agency
IoT	Internet of Things
IP	Internet protocol
ISTQB	International Software Testing Qualification Board
ITS	Intelligent Transport System
MoS	Motor ways of the Sea
PDCA	Plan-Do-Check-Act
PUE	Power Usage Effectiveness
SaaS	Software as a Service
SEEMP	Ship Energy Efficiency Management Plan
SSS	Short Sea Shipping
URL	Uniform Resource Locator
VDR	Vessel Data Recorder

WNN	Wavelet Neural Network

CHAPTER 1: INTRODUCTION

1.1. BACKGROUND

During 2007 – 2011 international shipping emissions was estimated to be 938 million tonnes of CO_2 and 961 million tonnes of CO_2e for GHG, combining CO_2, CH4, and N_2O (IMO, 2014). As at 1 January 2018, the World commercial fleet consisted of about 94,171 vessels, with total tonnage of 1.92 billion dwt, transporting large volumes of products to various destinations (UNCTAD, 2018). Due to increasing population and living standards, leading to growing demand for goods, seaborne trade is anticipated to increase from 2018 – 2023. Therefore, aside from implementing measures, monitoring and management of ship energy efficiency is paramount, as improper management would mean an increase in greenhouse gas (GHG).

Several moves have been made towards the ambitious goal of the IMO. At the 72nd session of the Marine Environmental Protection Committee (MEPC) meeting held in April 2018, IMO adopted a strategic vision to decarbonize the shipping sector. Its plan is to first reduce total GHG by at least 50% by 2050 compared with 2008 levels while pushing for a total phase-out (IMO, 2014). One of its clear targets is to reduce carbon intensity to a minimum of 40% by 2030 and 70% by 2050. IMO also deliberated on the introduction of Market-Based Measures (MBM), such as emission trading systems and carbon levies (UNCTAD, 2018), as a strategy to compel ship owners to be vested in reducing CO_2 emissions from their ships.

The special Intergovernmental Panel on Climate Change (IPCC) report, “Global Warming of 1.5 degree”; released on 8 October 2018, notified Policy makers of the current impacts of climate change. It highlighted the need for rapid reduction of carbon emissions by a minimum of 49% of 2017 levels by 2030 and encouraged work towards neutralizing carbon by 2050 (Intergovernmental Panel on Climate Change, 2018). The finality is to reverse the effects of climate change. This herculean task may require National Governments to align with international climate change experts to develop and implement a strategy aimed at achieving this goal, noting that it would involve quick dramatic changes to the functions of businesses and societies.

The IMO has proactively developed strategies for the maritime sector, such as the Sulphur Cap 2020 regulation. It requires a substantial reduction of SO_x from 3.50% m/m (mass by mass) to 0.50% m/m effective 1st January 2020 (IMO, 2018).

Another strategy is the implementation of the Data Collection System (DCS) that commenced on January 2019. The DCS process requires ship owners to include a Data Collection Plan (DCP) in their Ship Energy Efficiency Management Plan (SEEMP) Part II by 31 December 2018 (IMO, 2018). When a DCP is included in the SEEMP, it is approved and confirmed by the verifier. Upon confirmation, a Confirmation of Compliance (CoC) is issued to the ship owner. The next stage is the actual data collection by the ships in-line with the DCP. After the collected data is submitted, the ship owner is issued a Document of Compliance and then a Statement of Compliance after verification and entry into the database by the Administration. All these processes should be completed on or before 31 March 2020.

To aid data collection, IMO launched the Ship fuel database, Global Integrated Shipping Information System (GISIS). GISIS is used to collect data from international vessels through states. The information shall be collated to build historical information for ships, and analysed and used to develop a baseline for ships and their corresponding CO_2 emissions. More time is required to assess the efficacy of these measures and strategies.

Looking forward, as the Fourth Industrial Revolution (4IR) approaches it comes with swift disruptive technology concepts, and the current gradual phase out of traditional operational methods, automatic data collection, communication and processing may aid the process. Some ship owners, companies and operators have already embraced the concepts of Internet of Things (IoT), Artificial Intelligence (AI), Blockchain Technology, and Big data to improve work processes and monitor fuel consumption.

Some examples are:

1. The “Electric Blue’, a future ship concept produced by Rolls-Royce (Levander, 2017)
2. Cargo visibility from any part of the world used by Maersk
3. The use of drones by operators to monitor emissions
4. Denmark’s Explicit Marine
5. The UK’s Martek Marine
6. Class NK and Napa fleet intelligence (NAPA Green, 2019).

Although these concepts rely on data collection, communication and processing techniques that utilize high computing resources, the benefits cannot be over-emphasized.

1.2. PROBLEM STATEMENT

The entry into force in January 2013 of the EEDI and SEEMP created a platform for further research into energy efficiency measures in ship design and operations. The EEDI is a ship technical measure aimed at promoting the use of energy efficient equipment and engines for new ships. The SEEMP relies on the Energy Efficiency Operational Indicator (EEOI) that is supposed to be a monitoring tool used to manage ship and fleet energy efficiency performance. It was anticipated that after a period of implementation of the SEEMP, the indicator would give the operators a guide to where improvements would be introduced.

A previous study by Smith, O'Keeffe, Aldous & Agnolucci (2013) identified low improvements and proposed a tri-solution approach. The authors highlighted that proper attention should be paid to the underlying physics that affect ship performance, uncertainty of input data sources and use of new and quality data sources (such as Automatic Identification System (AIS)). After the entry into force of SEEMP, Olmer, Comer, Roy, Mao, & Rutherford (2017) yet realised an increase in emissions. Ghaforian (2018) thus conducted a deeper root cause analysis of SEEMP ineffectiveness and identified 3 classes of barriers, management, economy and uncertainty of EEOI, and introduced a ship energy management self-assessment (SEMSA) using Energy Management System (EnMS) ISO 50001 approach as a solution to improve the efficacy of the SEEMP rather than reliance on the EEOI. As part of the further barriers identified in Kitada & Ölçer (2016) and recommended solutions in Smith et al (2013) and Ghaforian (2018), the aspect of monitoring was a salient point because it provides deep insight into the definition of operational barriers and stimulates continual improvements, which could result in achieving the ambitious targets of the IMO and by extention the IPCC.

In recent times, the advent of the fourth industrial revolution (4IR) in shipping has promoted the use of technologies for data collection, including IoT, sensors, cyber physical systems (CPS) and data analysis, such as big data analytics applications, to help monitor ships in operation and provide real-time decision support to offshore crew and also the stakeholders ashore.

The complete autonomy in ship operations will demand much more complex data analysis and storage for real-time monitoring and decision making, which may be achieved with big data analytics, AI and adequate communication infrastructure.

In current times, large data sets are generated, analysed and stored at data centers to guarantee 24/7 accessibility by offshore and onshore staff and stakeholders. DNV-GL in conjunction with NAPA released a Software as a Service (SaaS) application to optimize ship operations with the of use digital twin information of ships and connection to a minimum of one data collection system on board a vessel. One method of ensuring uninterrupted provision of such services is to deploy the application on a reliable and resilient data center.

In addition, the anticipated increase in seaborne trade and increase in modern vessel construction depict more demand for computing, storage, digitalization, connectivity and proper monitoring. Obviously, Shipping 4.0 business decisions may depend on data center availability amongst all other factors.

In 2018, 1752 of 4458 colocation data centers in the world were located in the USA, representing about 39% of the total. In 2016 more than 90 billion kilowatt-hours were used yearly by U.S data centers, while global datacenters used 416 terawatt-hours yearly, and it was projected to increase every four years. Contrary to the projections in 2016, a drop in emissions was recorded in 2017 and 2018 with a benchmark of 2015 emissions. Currently, 2019 emissions are reported to have declined from 2016 and are further predicted to drop in 2020 (International Energy Agency, 2019).

As seen in Figures 1-4, data center emissions decreased but the data center workloads increased which is a function of Internet traffic.

With recent developments in application of big data to improve ship operations and the gradual migration to full ship autonomy, it is obvious that computing workload related to ship operations will increase. This will require more storage and real-time processing. An early look at the volume of emissions caused by the use of big data and AI tools shall prevent the likelihood of these technologies becoming another indirect energy related cost due to indirect emissions as a result of using these tools.

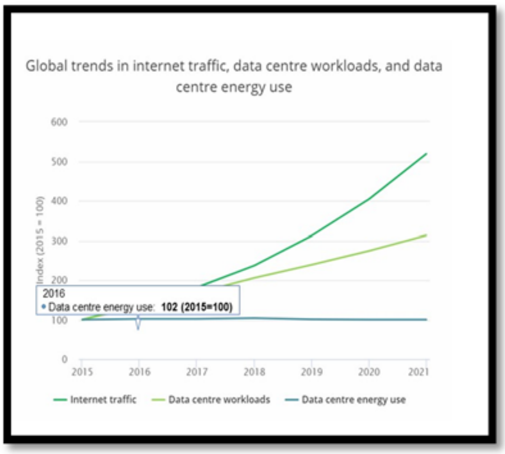


Figure 1: Data Center energy use in 2016

Source: International Energy Agency, 2019

(https://www.iea.org/tcep/buildings/datacenters/)

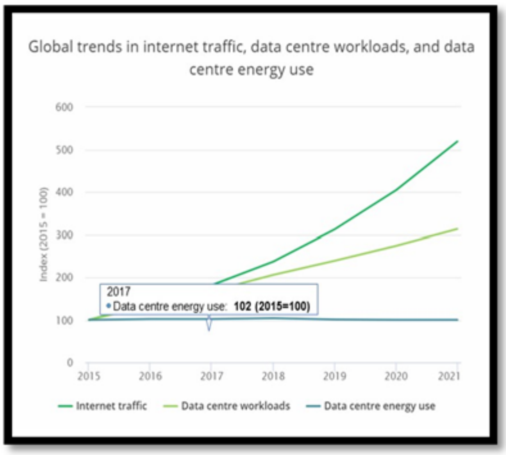


Figure 2: Data Center energy use in 2017

Source: International Energy Agency, 2019

(https://www.iea.org/tcep/buildings/data centers/)

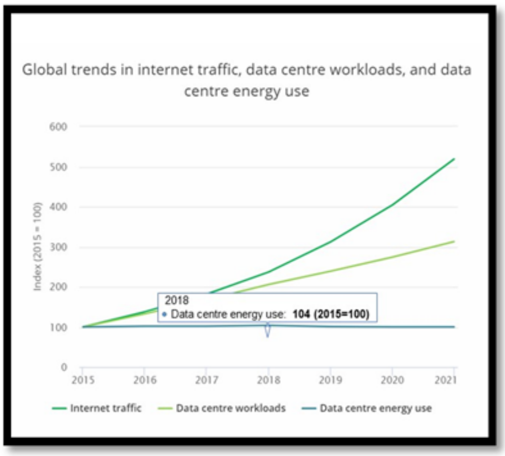


Figure 3: Data Center energy use in 2018

Source: International Energy Agency, 2019

(https://www.iea.org/tcep/buildings/data centers/)

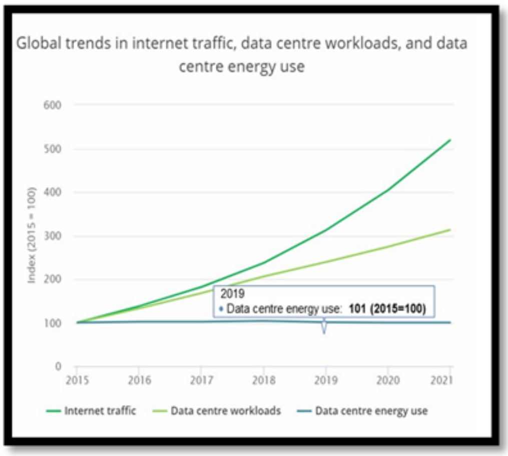


Figure 4:Data Center energy use in 2019

Source: International Energy Agency, 2019

(https://www.iea.org/tcep/buildings/data centers/)

A Data center comprises of the cooling system, racks, power supply units, servers and other computing devices. The power usage effectiveness (PUE) is a preferred metric for rating a data center, it measures the data center infrastructure efficiency with respect to the electrical load of IT devices (WSP Environment & Energy LLC, Natural Resources Defence Council, 2012), however, the scope of this research is limited to the power consumed by the server component of a data center.

This novel research identified various external and on board sources of big data required for ship operations. It also described the development process of a tool (emission calculator) to estimate the power consumption of the server and its corresponding CO_2 emission used to aid ship operations of a test ship. Lastly two (2) major models were created, and their energy consumption and corresponding emissions for ship and server were analysed. It was proved that CO_2 emissions generated from big data processing were considerably low and can be optimized.

1.3. RESEARCH AIM AND OBJECTIVES

1.3.1. AIM

The purpose of this study is to develop an estimation tool to assess the amount of CO_2 emission contributed by the use of big data analytics for ship operations. This research is aimed to achieve the following objectives:

1. Identify the sources of ship operational data used for big data analytics.
2. Conduct a requirement elicitation for the development of the emission calculator.
3. Design the emission calculator graphical user interface (GUI) using Netbeans IDE 8.0.2 and DataGrip 2019 2.3 database management system (DBMS).
4. Use java programming language to develop main classes and connect forms to the database.
5. Test and validate fuel consumption of a test ship against results from the TEFLES module (European Commission, 2017).
6. Develop a model that can be used to show the energy consumed as a result of using big data (real-time) analytics applications to monitor ship operations.

1.3.2. SIGNIFICANCE

This research estimates the CO_2 emission contributed indirectly by a server in a data center using real-time applications workloads for a single voyage. The emission calculator developed may be used to calculate energy consumption from the ship and the server and their corresponding CO_2 emissions.

A guideline, standard for acquisition or subscription for big data applications used in ship operations by ship owners may also be developed.

The research results could be used to establish a clear case of CO_2 emission rate that would be contributed by the use of big data in the 4IR.

1.3.3. RESEARCH QUESTIONS

The following questions will be addressed by this research:

a. What are the various sources of ship operational data that can be used for big data analytics?
b. What is the structure of the model used to show energy consumption and CO_2 emission of a ship in operation relative to that of the server used to host the monitoring application?
c. What is the quantity of CO_2 emissions from servers that use big data analytical application for ship operations for a voyage?
d. What processes are required to create an emission calculator for the measurement of CO_2 emissions derived by the use of big data applications?
e. When a fleet is part of the constituent of the model, how much CO_2 emission is generated?
f. Is the quantity of CO_2 emission resulting from big data analytics application commensurate to the value provided and how does this affect the global target of emission reduction?
g. How can we efficiently reduce the server CO_2 emissions caused by ship operation in view of Shipping 4.0?

1.4. RESEARCH METHODOLOGY

The mixed research method was used, which is a combination of qualitative and quantitative research techniques, methods and approaches. (Johnson & Onwuegbuzie, 2004). An overview of how the mixed method is applied in data collection and processing is depicted in Figure 5, and a detailed explanation is provided in the sub sections that follow.

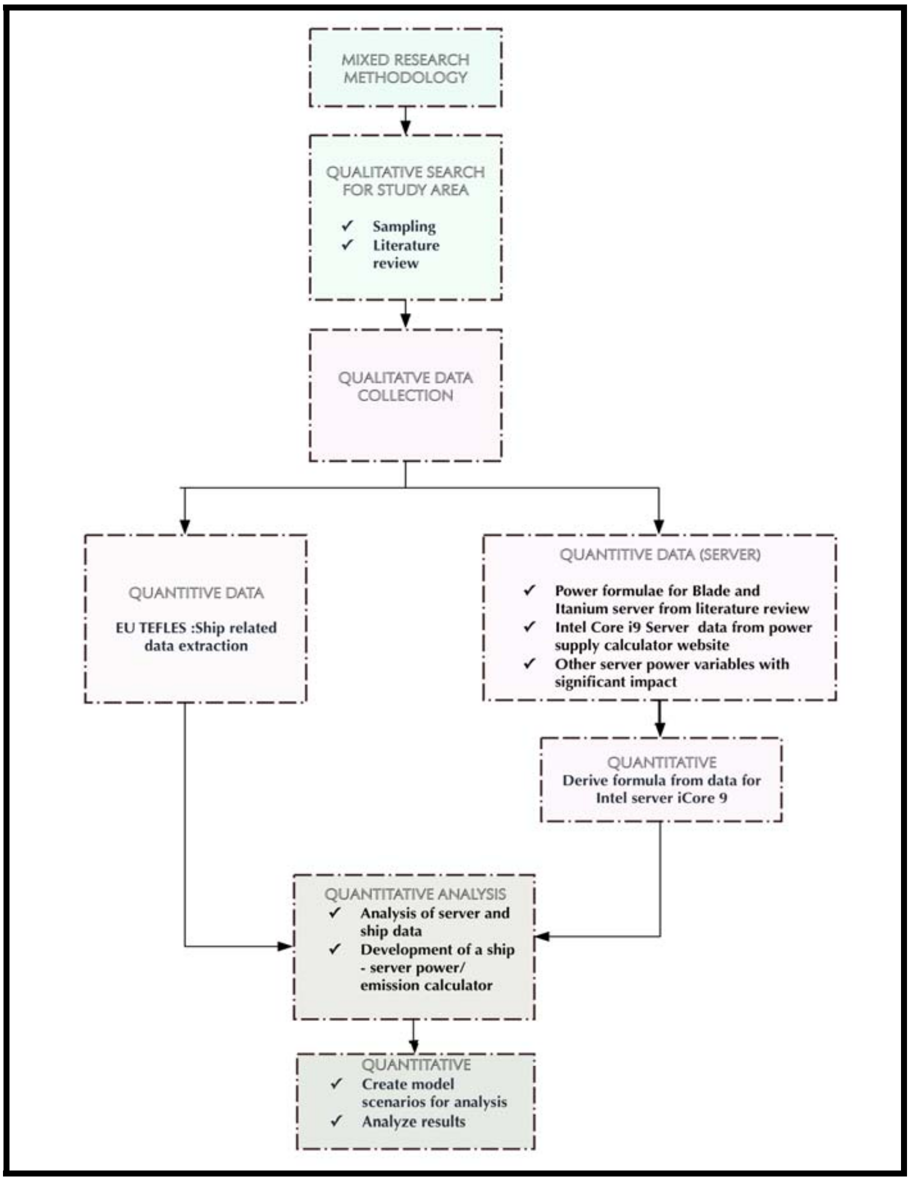


Figure 5: Research Methodology Process

1.4.1.1. DATA - QUALITATIVE RESEARCH

Literature review method was used to determine if any work regarding the subject matter had been conducted. It was found that various studies had focused on the benefits of big data processing and identified several challenges, especially cyber security. Data center and server energy efficiency was addressed by a limited number of sources but none directly applied to ship operations.

The scope definition of this research was streamlined to ship operations and data center power consumption. Further research revealed that data centers were comprised of several significant energy uses (SEU), such as the cooling system, server and rack amongst others. The server was selected as a major component because it is the major device that handles storage and processing of collected data. The benefits big data application and current trends show that data would be the next most important resource in future. Thus the usefulness of large datasets stored on the server cannot be quantified, as it could be applied to various scenarios and used in many dimensions. Moreover, it was important to identify other factors, such as the power user effectiveness (PUE[1]) and the location of the data center. The location of the data center determines the carbon factor and carbon intensity, which greatly influences the quantity of CO_2 emissions. In summary, the following were determined:

i) The sources of data for ship operation
ii) Factors that determine the fuel consumption of a ship in different operating modes
iii) Factors that determine the CO_2 emission of a server in a data center,
iv) Computing workload on servers
v) The requirements for the development of the CO_2 Emission calculator
vi) Appropriate component for the model design

Studies were reviewed, summarized and a combined corpus of research on ship energy optimization, the use of IoT, big data analysis, server power optimization and data center efficiency was completed.

1.4.1.2. DATA COLLECTION – MIXED RESEARCH

Literature review method was also used to collect quantitative data. More insights about the European Union (EU) sponsored project, Technologies and Scenarios for low Emission Shipping (TEFLES) were gained. The EU had a target to cut down 60%

[1] PUE an energy efficiency metric, it measures data center efficiency relative to the electrical load of its IT equipment. The ideal PUE is 1.0

of its carbon emissions by 2050, and thus sponsored TEFLES project. It was focused on ensuring that Short Sea Shipping (SSS) would be more environmentally competitive. In the project, various scenarios at sea, in coastal areas and ports were captured. Several after-treatment, hydrodynamic and power-generation technologies for emission reduction in ships were also captured and analysed. The TEFLES project file was used because all workable scenarios for the performance of engines of 20 ships were already available. This data was used for analysis and development of the ship fuel consumption in the CO_2 emission calculator.

To determine the formula for the server, a literature review was conducted to understand the significant variables in server power calculation and determine what sources were available. Two server formulae - Itanium and Blade servers were extracted. For a more recent estimate, further research was conducted for data to derive a formula for a more recent server. Data was extracted from an online power supply calculator and used to derive a formula for an Intel Core i9 server. The workloads on servers when using different application types were also derived. In summary, as seen in Figure 5, the qualitative research method was used to collect quantitative data. The outcomes of the process are listed below:

i) Collection of 20 ship static data and engine information
ii) Distance of 4 Motorways of the sea (MoS)
iii) Power formulae for 2 server types
iv) Derived formulae for Intel Core i9 server
v) Appropriate component for the model design
vi) CPU utilization rates based on workload and application types
vii) Carbon factor and intensity based on location

1.4.1.3. DATA ANALYSIS – QUANTITATIVE

The Emission calculator was developed using Netbeans IDE 8.0.2, DataGrip 2019 2.3 tools and java programming language. Tests were carried out to validate the results from the CO_2 emission calculator. The workloads and equivalent central processing unit (CPU) utilization rates were used to create and implement two (2) models. Each model consists of 2 major components, the ship and the server. Quantitative data was derived after analysis and presented.

1.5. DISSERTATION OUTLINE

The dissertation comprises 6 sections as displayed in Figure 6.

As seen in Figure 6, Chapter 2 introduces the underlying concepts of 4IR and the relevance of big data analytics to ship operations. This is followed by a review of articles related to the 4IR concept and its application to ship operations. The shortfalls are highlighted to identify gaps. Chapter 3 describes the methodology used to develop Models for measurement of CO_2 emissions of a ship and server in a voyage. In Chapter 4, the software development of the emission calculator is discussed, and Chapter 5 evaluated the two model scenarios and also the discussed the results achieved when a different grid carbon factor is applied. The research conclusions, limitations and relevant work to be done are discussed in Chapter 6.

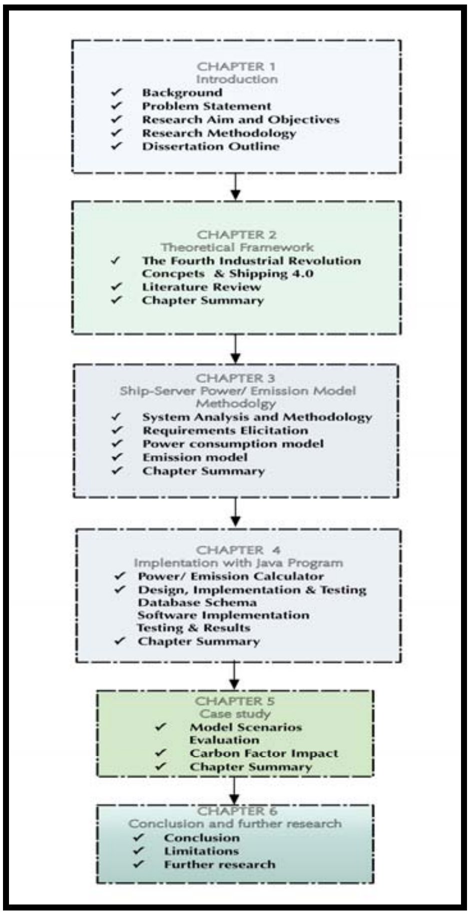


Figure 6: Summary of dissertation Flow

CHAPTERS 2: THEORETICAL FRAMEWORK

2.1. THE FOURTH INDUSTRIAL REVOLUTION CONCEPTS AND SHIPPING 4.0

The discussion below deals with the underlying concepts of the fourth industrial revolution, and a summary of the research conducted in-line with the subject matter is provided.

Technology played a major role in the transition from agrarian to industrialized society, which is known as the Industrial Revolution. The term first came in the lexicon in 1799 (Nardinelli, n.d.) and is generally known to have taken place between 1770 and the mid-1870s.The resulting technological change enabled humans to harness mechanical and electrical forces in their endeavours (Skilton & Hovespian, 2018).

Before mechanization, humans used their hands and animals to build, work, and travel - sails were used for ship transport. The successful steam engine, invented by James Watt, was used for powering manufacturing, production and agricultural machinery. In 1886, steam engines were capable of producing 10,000 horsepower and were used in large scale ocean steam ships. This was the first industrial revolution. By the end of the 19th century came the 2nd industrial revolution which saw industrial scale electrification and electric motors, the use of petrochemical combustion engines, mass production and globalization to meet with the increasing population. In the 20th century came the world war that lead to change in global power, the beginning of nuclear power and electronics, information systems, automation of manufacturing and production, telecommunication, new insights in biology, miniaturization, transportation, media and engineering and consumerization. The drivers were the Asian markets particularly China and India due to geopolitics, proximity of labour force, natural resources and colonisation (Skilton & Hovespian, 2018). This was termed the third industrial revolution, which in summary was a digital revolution characterized by the move from analogue mechanical technology to digitization. As for shipping, is it characterized by satellite guided navigation and digital transportation of information (Skilton & Hovespian, 2018).

The 4IR, often termed cyber-physical system, is based on interconnections between the physical, digital and biological sphere. It is characterised by extreme automation, connectivity of cyber physical systems driven by Artificial Intelligence (AI), Machine learning, and robotics. This technological breakthrough covers a wide range of fields such as 3D printing, nanotechnology, biotechnology, quantum computing, the Internet of things (IoT), and energy storage to mention a few (Schwab, 2017).

According to Lehmacher (2017), the 4IR is expected to bring networks of autonomous vehicles. One obvious factor to be considered for the successful transition to autonomy is the increasing need for energy. The first revolution reduced the use of human labour and directed the use of energy through mechanization to do more work. The same happened with the 2nd and 3rd revolutions, all in the bid to improve efficiency. The 4th industrial revolution, as it moves to autonomy, must be mindful of trade-offs. The use of cyber physical systems, artificial intelligence, and internet of things also require more energy, which will also lead to an increase in GHG emissions if not properly managed. The International Energy Agency (IEA) is already aware of the growing need for energy, thus they invest in research to discover sustainable fuels like hydrogen, biomass, geo-thermal, wind, solar energy and the like as the current energy reserves decline. Some important challenges such as storage, transport of fuel and the quantity available for sustenance are salient and require more time for solutions to be developed. For the immediate the best strategy is to generally improve energy efficiency and energy management.

The Energy Management Standards ISO 50001, which follows the PDCA (Plan-Do-Check-Act) cycle, emphasizes the importance of monitoring as one of its critical success factors. To monitor energy consumption, it is required to first identify significant energy uses (SEUs), and identify the baseline consumption pattern and related variables that can affect the identified baseline. Then areas for energy efficiency can be clearly seen and methods for implementation derived. After implementation, the need for monitoring is still sacrosanct to detect faults, understand the equipment / facility, verify if methods implemented produce the required results, and aid in making decisions (Standard ISO 50001:2011). The importance of monitoring cannot be over emphasized as it aids process improvements and creates visibility for the stakeholders and top management.

As for the shipping sector, EnMS ISO 50001 can also be applied to reduce energy consumption of ships in operation as illustrated in Ghaforian (2018); and to achieve shore visibility in near real-time, the use of some technology concepts is inevitable. AI, machine learning and robotics enabled by cyber physical systems characterize the 4th IR. Some of the 4IR terms as relates to shipping are briefly discussed below.

2.1.1. CYBER PHYSICAL SYSTEM

Cyber-Physical System (CPS) basically involve the integration of computation and physical processes. It utilizes embedded computers and networks to monitor and control the physical processes, and then provides feedback for computation where physical processes affect computation and vice versa (Lee, 2006 &Neuman 2009). It may have the capability to constantly store data at a high velocity and transmit data to other systems. An example is the AIS transponder, which is used to collect, store and transmit data. Such data can be used to provide insights to detect waste and faults, improve management of resources, develop policies, and develop new areas of research to mention a few.

2.1.2. BIG DATA

Data is classified as big data when it possesses features such as high volume, variety, velocity, value, veracity, variability, viscosity, and virality (Wu, Guo, Li, & Zeng, 2016). In a literature, Kazumazu (2016) stated that the success of the 4th industrial age is data dependent, which is evident in the shipping industry. Currently, electronic data is gathered by disparate systems installed by the ship owner to monitor cargo, operation, safety and performance. These data grow over time and are currently used to analyse, learn and predict systems and processes. Traditionally, Classification Societies have been the custodians of the vast amount of ship data and are crucial for successful transition to smart shipping due to the volume of data available.

An example is the ABS vessel performance service, it has data monitoring and collection capabilities and is supported by ABS nautical systems voyage performance software. It organizes the data into standard reports that can be acted upon without delay. The ABS system collects data variables such as speed, power, fuel consumption, voyage information, weather conditions, fuel switching, and wastewater handling. These data are collected and used to generate reports for statutory verification (Jan de Kat. ABS, 2017).

Koga (2015) focused on the Voyage Data Recorder (VDR), one of the sources of data on board vessels. He reviewed several definitions of big data, its features, scenarios for its application in maritime, the challenges to develop maritime big data, and proffered solutions. The application of big data analytics in shipping provides a platform for collaboration with ports, agents, regulators and ship operators. Big data analytics can be used to make decisions regarding vessel maintenance based on performance, such as use of fuel consumption data for cost-benefit analysis of vessel maintenance, including hull cleaning.

Ship big data are generated from sensors, CPS, IoT and other available ship data sources. Big data acquisition onboard ships consume relatively little energy for data collection and data transmission (Baldi, Johnson, Gabrielii, & Andersson , 2015). However, the conventional database applications software cannot properly handle the storage of various kinds of big data, thus, advanced technology storage was designed to handle big data. Its repository is most often located offshore at a data center which consumes more energy in relation to ship big data acquisition.

As more ships seek better monitoring and gradually migrate to autonomy, it is anticipated that ship big data analytics will face the challenges of large-scale data analytics. Although parallel framework and architectures are most appropriate to process big data, these processes give rise to more consumption of energy and other resources. The growth rate of IoT, data, computationally intensive big data analytics and processing may increase energy consumption, thereby increasing GHG emissions.

2.1.3. BATCH PROCESSING

This is one of the techniques used for processing historical data. It is used for scenarios that are not time-critical such as training procedure for most machine learning algorithms. This form of processing is necessary for widely shared resources and is very efficient due to the offline processing mode and flexibility in processing time. The batch size can affect the efficacy thus it is necessary to know the maximum processing limit of a batch processor. Vouros, et al.(2018)

2.1.4. ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI), refers to computational tools that utilize data generated from physical work processes for the purpose of efficiently performing such tasks either in similar conditions or newly learned conditions. It uses big data captured by CPS or other means to analyse relationships between variables, learn patterns / build models and predict situations – in essence automate tasks. The training process is known as machine learning, which is discussed below.

2.1.4.1. MACHINE LEARNING

This concept is associated with Intelligent systems / Agents, which exhibit the ability to adapt or learn from experience and respond to their environment, thus elevating the agent to a higher level of ability (Skilton & Hovespian, 2018).

Machine learning tasks are of two kinds: classification and regression. Classification basically categorizes data into sets that have a family resemblance, while regression aids that system to make a prediction based on extrapolated data trends. Machine learning has the potential to solve categories of learning problems such as classification, clustering, regression, and optimization. Various types of machine learning exist, namely supervised learning, unsupervised, model-based, memory based, deep and reinforcement learning. The machine learning lifecycle comprises of these iterative processes:

1. Goal definition, identification of problem type
2. Data collection and training
3. Create/design the model, evaluate and optimize the model
4. Check if the model can make a valid prediction and its performance with new data

Machine learning algorithms are based on single layer perception (clustering, decision trees, dimensionality reduction, kernel approaches, Bayesian, regression analysis and deep learning) and multilayer perception (Neural network) (Skilton & Hovespian, 2018) can be applied in this research depending on the varying factors that determine the energy consumption of ships.

2.1.5. SATELITE COMMUNICATION SYSTEM

In the 1800s, transatlantic cables were installed for the capability of the ship to shore communication, which was limited to voice, telex and morse (DNV GL, 2015). In the 1990s, satellite communication was introduced to support the Global Maritime Distress Safety System (GMDSS) for digital communication. However, mid-2012 the capacity of the transatlantic system was 49.5 Terabytes per second (Tbps). As a result of improvement of communication methods with the use of sensors and data analytics, we now have connected vessels. Ship connectivity creates a platform for data to be collected and retransmitted. The drivers of these developments were distress and safety, navigational aids and reporting, operational applications, welfare, and entertainment.

2.1.5.1. INTERNET OF THINGS (IoT)

Internet of Things refers to connection between the digital and physical world. According to Ray (2018), it is a collection of numerous active physical things, actuators, sensors, cloud services, specific IoT protocol, communication layers, users, developers and enterprise layer.

The IoT system requires a communication protocol for data exchange amongst devices. An IoT should have dynamic and self-adapting capability, and ability to self-configure, support interoperable communication protocols, possess a unique identifier such as Internet protocol (IP) address or Uniform resource Locator (URL), be context aware, make intelligent decisions and be able to integrate into information frameworks (Sebastian & Ray, 2015). Two examples of IoT devices in shipping are, the Kiber helmet, which is used to support engineers offshore and drones used for sniffing CO_2 emissions

2.1.5.2. CYBER SECURITY

When data is made available over a network and is strongly relied upon for feedback and decision making, there is a need for security to avoid cyber criminals such as war divers and Distributed Denial of Service (DDoS) to mention a few. In 2017, 33% of businesses were reportedly affected by DDoS. Moreover, a Danish Shipping survey discovered that 69% of Shipping companies experienced cyber-attacks in 2017.
Several cases were reported, such as the IRISL (Islamic Republic of Iranian Shipping Lines) 2011, Saudi Aramco Oil and gas Operator in 2012 and Danish Maritime Authority, 2012 (Miranda, 2018). This indicates the importance of protecting data to avoid manipulation and loss. The IMO has already taken action. In the 94th session of the MSC meeting, on agenda 4 in 2014, Canada and USA co-presented a proposal to be adopted by the committee: Measures towards enhancing maritime cyber security. In this document, the committee was requested to develop voluntary IMO cyber security guidelines. In 2015, co-sponsors BIMCO, ICS, INTERTANKO and INTERCARGO also proposed that the committee develop industry guidelines on cyber security on board ships at the 95th session of the MSC meeting in 2015. At the

98th session the guidelines were approved and will enter into force on January 2021 (IMO, 2017)

2.2. LITERATURE REVIEW

Several studies have been conducted to demonstrate the use of big data in the optimization of energy consumption during ship operations and, conversely, measure its indirect contribution to GHG.

Koga (2015) reviewed DNV-GL, LRF and e-Navigation interpretation of big data, and identified and categorized four (4) major challenges, Sound competitive conditions, Technology, Human Resources and Security, for which he proffered solutions. Also Rødseth, Perera, & Prasad (2017) identified seven (7) sources of big data for ships, discussed eleven (11) problem areas, categorized the data sources and related problem areas and proferred solutions to some. The authors further discused three (3) axes of management of ship data on and off shore, and the use of principal component analysis (PCA) for data compression (volume and storage axes). On the data quality axes, outlier detection, understanding sensor systems, and statistical and trending methods were used to check for quality.The third axes, data analytics dealt with the transformation of data to information with the use of existing models / hypothesis and use of statistical techniques to determine relationships between parameters, and machine learning techniques for classification and regression analysis.

Gonzalez, Lund, & Hagestuen (2018) also did not use data from noon reports due to the level of accuracy, rather data was sourced from a ship performance management (SPM) application collected via various flow meters, which captured data at a high frequency of 15 seconds (in-line with ISO 19030) and averaged every 15 minutes. Relevant parametric analysis was conducted and used to determine ship operational performance. Two LNG sister ships with dual fuel engine were used as a case study to determine which was more time efficient and energy based on the analysis of high frequency data collected. Excerpts from the analysis shall inform the ship operator of which ship is more energy efficient.

Aldous (2016) considered various performance optimization models, including real-time optimization and developed an uncertainty framework for ship performance. Relative uncertainty of noon reports and continuous monitoring based methods were compared, and performance models were tested. Data to understand the generalities of ship performance were analysed and a hybrid model for monitoring ship operational performance was developed. This was used to quantify the total uncertainty of the ship performance indicator and was validated with datasets from continuous monitoring and noon reports. In the report, speed sensor and sample size parameters were shown to improve precision and speed sensor trueness whilst sample averaging frequency parameters reduce precision, and finally showed that with continuous monitoring the uncertainty achieved was tenfold better than the use of noon report in combination with other data acquisition parameters.

Perera & Mo (2016), focusing on data management, proposed the compression of big data identified by machine learning, the data classification (with the use of Gaussian mixture model -GMMs) of a marine engine during operation and the implementation with an algorithm called Expectation maximization (EM). This compressed data was transmitted to shore and expanded with the use of auto-encoder (deep learning a machine intelligence technique). Then an integrity test was conducted on the ship-expanded data and concluded with a data regression process in which expanded data points were used to estimate the needed parameters for navigational and ship performance information. Information derived from this process could aid decision making as relates to energy efficiency in ships. Similarly, Chaal (2018) carried out a study using a VLCC case ship, where machine learning tools and black box method were used to develop ship operational predictive models and optimization with genetic algorithm. Four (4) models were compared: Decision tree, AdaBoosted decision tree, K- Nearest Neighbor and Artificial Neural Network, and the ANN model produced the best result. The project demonstrated the optimization of ship voyage by minimizing fuel consumption.

Vouros, et al.(2018) proposed datAcron system architecture for real–time big data analysis incorporating aviation and marine transport data, which computes statistical data like speed and/or acceleration. All data sources were represented in a knowledge graph. Real-time prediction of data manager, trajectory detection and visual analytics were also included. The use of Patern Markov chain was suggested for streaming data, and machine learning for archived data to build prediction models. DatAcron used Apache Flink for processing stream components, Apache Spark for batch processing and Apache Kafka for communication in real-time. However, the focus was on trajectory for Air Traffic Management (ATM), while Mirović, Miličević, & Obradović (2017), discussed improvements achieved with big data application for road transportation.

Kurashiki (2016), top classification society, ClassNK in conjunction with NAPA Green, CMAXS LC-A. and ShipDC developed big data smart tools with a 3 step approach; maintenance assist, operation assist and IT platforms. These tools can use data from ECDIS, VDR, engine data logger, ballast control system to optimize trim, monitor performance, engine performance, and remote maintenance in real-time and feedback transmitted to ship yard, engine manufacturer, ship equipment manufacturer and other related stakeholder. However an energy life cycle analysis (LCA) was not carried out as this would deomnstrate if techniques used to develop these solutions are equally energy efficient.

Amini, Gerostathopoulos, & Prehofer (2017) proposed a comprehensive architecture to analyze big data for real-time traffic control - Intelligent Transport System (ITS). The architecture deployed batch analytics processing and stream analytics for historiscal and live data, respectively. Tools like Hadoop Distributed File System (HDFS) and Cassandra were selected for batch processing while Kafka, Flink and Spark were used for stream processing.

Ahmed (2014) utilized Apache Flux to collect live data, apache sqoop to transfer data to Hadoop for batch pre-processing. Data was then processed with Apache Hive, Apache Pig and Cloudera Impala. Also Apache Mahout and Cloudera Oryx was used to mine data; R was used for statistical analysis and to determine energy efficiency. However, this was applied for buildings not ships.

Perera (2017) proposed a data handling framework rather than the conventional mathemathical model to overcome some big data challenges. It was supported by top down and bottom up approaches of the e-navigation framework (with AIS) and integrated bridge system (with navigation and ship operation performance data), respectively. The framework had 2 parts, data pre-processing and post- processing. The earlier consists of on-board application supported by a data model. In real-time the model should handle sets of big data in a flexible manner and it exists in a three dimension vector space. The result could be used for energy efficiency and applied to system reliability in the visualization layer.

Wang, Yan, Yuan & Li (2016) used Wavelet Neural Network (WNN) to predict the working navigation condition and real-time optimization method of ship energy efficiency (EE), through the use of established ship EE optimization model. Wavelet analysis is based on mathematical theory and WNN, characterized by self learning and fault-tolerant of nueral network. Its challenges cannot be ignored such as complex construction and dimension disaster.

Kai Wang et al (2016) illustrated that in an ideal situation, once the real-time engine speed is derived, a reduction of the fuel consumption per unit distance by 19.04% and lowering engine speed can improve energy efficiency. Additionally, short distance ahead of ship related to navigation environment factors was predicted with the Wavelet Neural Network (WNN) method and best speed for optimal energy efficiency was derived, thus real-time optimization under different navigational environmental factors was achieved.

Noting the role of big data acquisition, Gonzalez, (2017), Kyma vessel performance analyst examined the role of the VDR in the analysis of ship performance. The VDR is a piece of equipment installed on most ships since 2002 (SOLAS 1974); it records data during a voyage. It is used for data analysis when an accident occurs. Some VDRs interfaces with many ship sensors that are used to collect data for ship performance analysis.

Rødseth, Perera, & Prasad (2016) highlighted one of the major characteristics of Shipping 4.0, which is cyber physical system (CPS) and big data. Various data sources that generate ship big data were identified, such as bridge data network, conventional automation, CPS, ship performance monitoring, ship reporting, external ship monitoring system, weather data and port call. It also reviewed several issues in collection of ship data, such as context dependent data quality, safety and security, data entry errors, measurement of complex external phenomena, wilful errors in report for commercial reasons, data integrity, proprietary and costly interfaces to data, ownership of special or derived data, lack of interface standards, artefacts in AIS base stations, satellite reception and cyber security issues. Some solutions proffered were volume and storage management, ship-shore communication, improvement in data quality, use of big data for data analytics to achieve online ship decision support, ship performance optimization, fleet optimization, and predictive analysis to mention a few.

Discussions around big data challenges and solutions mentioned above excluded one view point; ***"quantity of emissions passed to data center by storage and processing of big data for ship operations".***

While Ship operators strive to reduce fuel consumption due to the cost of doing business and thus utilize big data to achieve this, the Computing community also shares a common challenge. Economou, Rivoire, Kozyrakis, & Ranganathan (2006) carried out an investigation to quantitatively understand the power consumption trend at a system level. They used the Mantis method, which is a full system power modelling technique to derive a formula for an AMD Turion blade server and an intel Itanium 2 server. The Mantis power model was applied and the model prediction accuracy ranged from 0 -15% for both servers. Their aim was to use this infromation to accurately predict the consumption of a server.

Similarly, Fan, Weber, & Barroso (2007) discussed data center cost, which was not related to the amount of energy used but rather to the amount of peak power consumed. Thus, the need for efficient utilization for the peak power was identified. It was observed that between the actual and theoretical aggregate peak power usage, a gap of 7-16% was identified at the cluster level and grew to almost 40% at the datacenter level. With the identified gap, two power savings approaches were presented, CPU voltage/frequency scaling (DVS) and improving non-peak power efficiency. The CPU DVS analysis showed that with a websearch workload the DVS produced a larger reduction relative to total power when compared to webmail and mapReduce workloads. The second method showed that the idle power consumption of servers can be reduced, thus the idle power of the servers was set at 10%. With this the maxiumum cluster peak power was reduced to 6-20% and corresponding energy savings ranged from 35% to 40%.

However, Zhu, Zhu, & Agrawal (2012) stated that a 300W high end server consumes 2628kWh yearly plus additional 748kWh for cooling and emphasized the amount of emissions this would cause. Then an approach for energy optimization in a virtualized system was presented. The pSciMapper, a power-aware consolidation framework which consolidates workflow tasks in a virtualized envirionment, was evaluated and results showed that 56% of the total consumed power is saved with a 10-15% performance slack.

WSP Environment & Energy LLC & Natural Resources Defence Council (2012) finally presented an energy management analysis that higlighted application of five (5) criteria that influenced the quantity of emissions from servers: Effectve utilization of server, server refesh rate, virtualization, power usage effectiveness (PUE) and carbon factor. The application of a combination of these criteria was demonstrated to provide a 95% decrease in emissions.

2.3. CHAPTER SUMMARY

Intensives studies ranging the sources of ship big data, techniques and architectural framework for processing them were reviewed. One of the most important challenges experienced from storing and processing such datasets - energy consumption, was identified. However, none of the studies conducted highlighted various industries' contributions and what measures could be taken from that standpoint to reduce emissions. Energy management attempts at the system and data center level were studied. Thus, the need to quantify GHG emissions as a result of using big data analytics applications in ship operation is imperative, especially as we approach Shipping 4.0.

CHAPTER 3: SHIP- SERVER POWER / EMISSION MODEL METHODOLOGY

3.1. SYSTEM ANALYSIS AND METHODOLOGY

The previous chapter highlighted major concepts of the fourth industrial revolution and identified gaps through an intensive literature review. In this chapter, the energy consumption model and emission model are presented along with a discussion on how these models were derived. The Server workload for a ship using a real-time application is understudied and analysed. The output of the analysis is used to develop the power / emission model and scenarios described.

3.2. REQUIREMENTS ELICITATION

The first step was to understand the data acquisition system during ship operation. Data acquisition comprises of ship data generation, acquisition and communication. Data from different systems on board a ship are collected in diverse formats, structured, semi-structured and unstructured format. Ships have various means and sources of generating data, from manually completed reports, such as noon reports, to large sensor networks (includes wireless sensor network), IoT on board the vessels and even CPS. Some examples are VDR, Marine Cyber Physical Systems such as dynamic positioning, vessel management, and propulsion management, AIS, IBS Integrated Bridge System (IBS), ECDIS, flow meters and others.

According to Raptodimos, Iraklis, Gerasimos, Takis, & Leonidas (2016),main sources of big data are enterprise data, data such as vessel traffic information, weather, the greater percentage of which are not generated from the ship but important for the ship operations voyage. The energy consumption of data generation and communication devices on board ships is accounted for in the vessels' fuel consumption.

Noting that the various sources of data for optimizing ship operations during a voyage affect the workload performance on the server, a brief overview of various data sources was conducted to identify the data type and need.
For the project, more insight on the data sources helped to determine what kind of application workload on the server would be deployed.

The total energy consumed would be the addition of the energy used by IoT, CPS, and sensors to generate data, energy used for transmitting data collected and the energy used to store, process and manage collected data.

Some ship data sources were identified and are discussed below.

3.2.1. MARINE ANEMOMETER

The anemometer is used to measure wind speed; the accuracy of measurement depends on the ship hull and superstructure. Its error rate of about 10% depends on the position of the anemometer (Moat, Yelland, Molland, & Pascal, 2005).
Suggested positions are above the platform, above the deck – on foremast in the bow of the ship, at a distance over three times the mast diameter from cylindrical masts, but ideally above the front edge of the bridge. Wind speed is measured in meters per second (m/s) thus large data sets are generated within 1 hour.

3.2.2. INCLINOMETER

The electronic inclinometer used on a ship measures pitch angle, heel angle, roll period, and amplitude (port and starboard). It should be in-line with IMO performance standard MSC.363 (92) and functional compliance, additional BSH type approved by IEC 60945 (Environmental condition). The inclinometer must be powered from the ships main power source. The possibility to operate it from the ship's emergency electrical source should be there as well as the possibility to integrate with other systems, such as the VDR. The electronic inclinator sensors should be accessible by the VDR and provide data at the rate of 5Hz. The data accuracy rate should be, for angle measurement, 5% of reading or ± 1 degree or whichever is larger, and for time measurement, 5 per cent reading or ± 1s or whichever is larger. And it may also provide a warning that a set heel angle has been exceeded. It should have a digital interface, roll period and roll amplitude. (IMO, 2013).

3.2.3. VOYAGE DATA RECORDER

The VDR was designed originally for safety but in recent times it has been applied to improve ship operation performance. It records information continuously and in various formats. It keeps track of the vessel position, movement, physical status, date and time, speed and heading, command and control of ship over a period, bridge audio, ECDIS, echo sounder, main alarms, rudder order and response, hull (doors) opening status, speed and acceleration, hull stress, and wind speed and direction.

The VDR has a DCU that pulls all the integrated sources; it is made up of a data processing unit, interface modules and backup batteries. According to IMO MSC.333 (90), the VDR should be powered directly by the ship's main power, emergency power and from a reserved power source capable of 2 hour storage when electrical power fails. In this case, bridge audio shall record for a period of 2 hours, after which all recoding should automatically stop. The storage should have data items for at least 30 days / 720 hours on long-term storage and 48hrs on the fixed and float-free recording media else data may be overwritten. VDR which is akin to a "Black Box" on airplanes – stores position, movement, physical status, command and control of a ship over the period (IMO, 2002).

3.2.4. RADAR

Radar has been used for S-band and X- band frequency to navigate and is a very important component. It is mainly used for safety, but not within the scope of this dissertation. There are different applications of radars for vessel traffic management.

3.2.5. ECDIS

Electronic Chart Display and Information System uses AIS data, echo sounder, radar, and electronic charts – computer based navigation chart that is IMO compliant, it is used for continuous position and navigation safety information (IMO, 1995).

3.2.6. FUEL FLOWMETER

There are many types of fuel flow meters, which are classified based on the type of fuel, presence and output type, system of transmitting data, indicator availability and others. Some examples are Coriolis, thermal and magnetic induction devices (Korobiichuk, et al., 2015). It is used to determine fuel consumption, the fuel flowing into the engine is heated, then the distribution of temperature field created by the heater is measured. The changes of temperature field with engine fuel flow are determined by the definite functional dependence on fuel consumption value.

3.2.7. SENSORS

Data quality is the major issue with use of sensors for data acquisition on board vessels, but as highlighted in Aldous (2016), provided the sensor rate of data collection is high and continuous when compared to manual method of data collection, it definitely has more data quality.

Other data sources from a ship include engine data logger, echo sounder, speed log, exhaust gas analysers, VHF and ballast sensors.
Noting that there are several thousands of sensors on a ship and several data collection points, the scope will be limited to data sources related to energy efficiency during operation of a ship.

3.2.8. AUTOMATIC IDENTIFICATION SYSTEM

The AIS was initially designed for exchange of navigational information between AIS-equipped terminals. It has been mandatory since 2004 for all passenger vessels and all commercial vessel over 299 gross tonnage (GT) engaged in international shipping to carry a class A AIS transponder, while smaller vessels can have Class B AIS transponders. Ships equipped with AIS transponders can transmit ship data to the AIS-receiving stations (MarineTraffic network) and share it with the MarineTraffic database. The data are transmitted in packets. The formats of the packets are in NMEA sentences (64-bit plain text) that would have to be decoded to be understood. The MarineTraffic database receives and process data and stores the most important data including geographic data. It has a Global Positioning System (GPS) that receives vessel position and movements. Dynamic and static information is broadcasted at regular intervals automatically via a VHF transmitter with two channels 161.975Mhz and 162.025Mhz – 87 and 88 old VHF channels.

AIS data are grouped in 3 sections:

1. Dynamic information: This is subject to vessel position, speed, current course and rate of turn
2. Static information: Vessel name, IMO number, MMSI number, dimension
3. Voyage-specific information: vessel destination, ETA and draught.

After data is received form an AIS, it is processed and depicted on a chart plotter or on computers. It can be received by another AIS or by satellite Sat – AIS. Against the backdrop of specifically using AIS information for navigation, it is used for diverse aspects including ship monitoring and operation performance.

3.2.9. EXTERNAL DATA SOURCE

3.2.9.1. DIGITAL TWIN

The digital twin of a ship is a virtual copy of the physical ship, which shows all sensor networks and data sources. It gives information about engine performance and hull integrity, the use of a virtual model during operation that allows visualization of all important components, carry out analysis and improve the ships structural and functional components. With this concept, the operator can create visual models of the ship and systems, such as the engine, and record fuel consumption distributed to energy use, such as boilers, engine, and batteries.

A brief overview of the AIS dynamic data gave more insight into ship operations in conjunction with the digital twin data, weather and vessel traffic information. These are used to monitor ships in operation by DNV-GL /NAPA and We4Sea. The services offered require less installation on physical ships, requiring only a subscription; this is called Software as a Service (SaaS). One obvious need for effective provision of such a service is constant connectivity to the Internet; this would require a server located in a data center.

3.2.10. DATA STORAGE / DATA CENTER

After a review of the requirements for data acquisition and communication, it was identified that the ship accounts for power consumption during these processes. However, for data storage and processing, the shipping company's in-house server is used for such applications, which is then captured in their energy map. While companies that subscribe to a software as a service (SaaS) provider or host their servers at a data center, the energy consumed is accounted for by the CIO of the data center. However, noting the urgency to reduce GHG in all dimensions, the shipping sector should be aware of the kind of service they subscribe to and ensure that energy is optimized.

Figure 7 shows that total power utilized for big data analytics is comprised of energy consumed for data acquisition, transmission, processing and management. However, more focus would be on data processing and management. In data management, data is collected from various sources, formats and sizes, transformed to a structured collection and processed with the use of software applications. Data processing includes real time processing and batch processing jobs, which would be done on a server machine. For reliable accessibility, data centers are best suited for hosting such applications; however, they are big energy users.

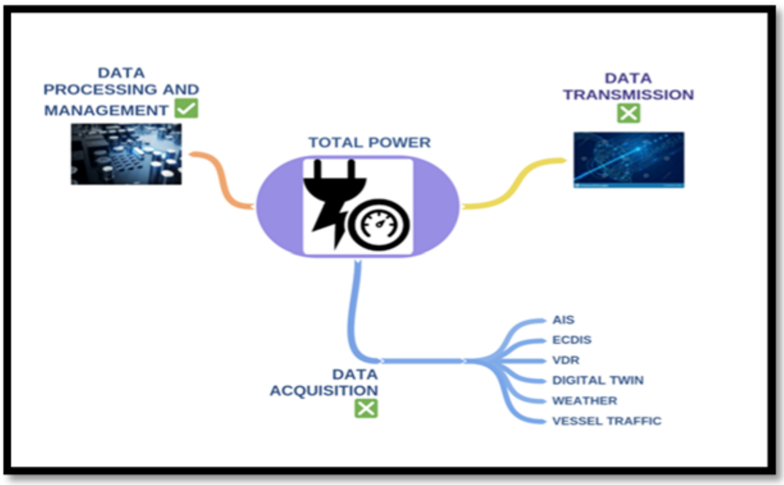


Figure 7: Total energy used for real-time applications in ship operations

3.2.11. SHIP- SERVER ANALYSIS

In order to identify specific parameters required for the calculation of emissions from a server located in a data center used for ship operation modelling, an Eriksson-Penker use case model (see Figure 8) was designed using Enterprise architect application.

In the diagram, the actor is a Ship operator / Ship owner whose aim is to determine how much power / equivalent CO_2 emission is used /generated by using big data analytics applications. The ship owner has already benefited from monitoring and controlling cost by using real-time big data applications. The case model is used to generate more questions that lead to more streamlined parameters.

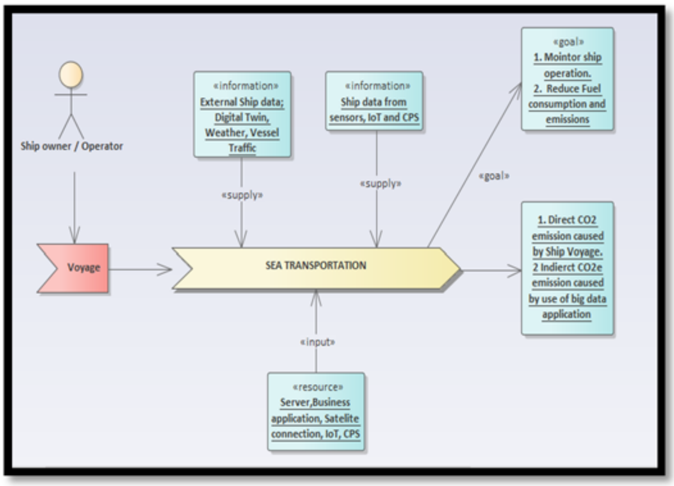


Figure 8: Eriksson-Penker use case model

From the use case scenario, a sequence diagram was developed to display the system boundary and other users of the application / tool. The sequence diagram is used to show clarity of the objectives of the application to all actors involved in the use of the application.

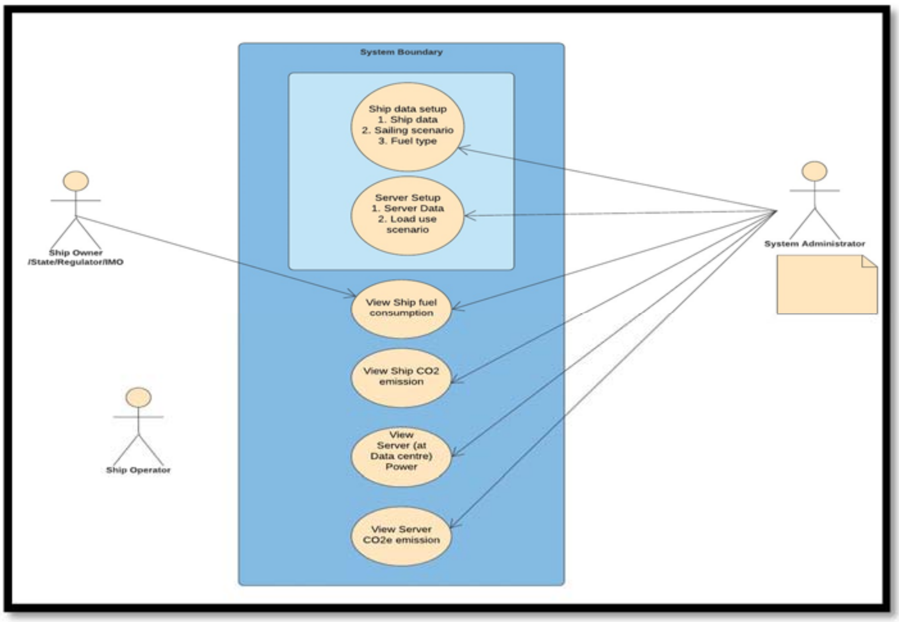


Figure 9: Sequence Diagram

From the sequence given in Figure 9, the tasks to derive the ship fuel consumption, server power consumption and their corresponding emissions were clearer.

The key understanding required were ship data required for calculating fuel consumption, emission and server formula for determining power consumption of the server and its corresponding CO_2 emissions.

3.3. POWER CONSUMPTION MODEL

The model comprises of two types,.one is a model for calculating the power / energy consumption of the server and the ship, while the second is the model for calculating the emissions as a result of the voyage.

3.3.1. SERVER DATA REQUIREMENT

For the computation of the Server power, three servers were selected. Two were from literature reviews, the AMD Turion processor (blade server) and Intel processor (Itanium server) with defined specification. This concept was used to derive a formula, as the most significant variable detected was the CPU utilization rate. The formulae below show the variables that relate to power:

$$P_{blade} = 14.45 + 0.236. U_{cpu} - (4.47E - 8). U_{mem} + 0.00281. U_{disk} + (3.1E - 8). U_{net}$$

$$P_{itanium} = 635.62 + 0.1108. U_{cpu} + (4.05E - 7). U_{mem} + 0.00405. U_{disk} + 0. U_{net}$$

Where U_{cpu} = CPU Utilization

U_{mem} = off-chip memory access count

U_{disk} = Hard disk I/O rate

U_{net} = network I/O rate

Extreme Outer Vision (2019) is an online application that provides power estimation for server systems. It was used to generate data. The selected server had the specifications shown in Table 1:

Table 1: Intel Core i9 Server specification

S/N	SYSTEM	Intel Core i9-7900x Server
1.	CPU	3.3GHz Vcore1.2V
2.	Memory	4x4GB DDR4 module FB DIMMS
3.	Storage	4 Sata 7.2k RPM

With the online application, 66 runs were carried out to extract the following data in Table 2:

Table 2: Data collection - Required power for Intel i9 server at different utilization rates

COMPUTER UTILIZATION TIME (HR)	CPU UTILIZATION (%)	UPS RATING (VA)	PSU WATTING (W)	POWER (W)	POWER (kW)
1	100	650	362	312	0,312
2	100	650	364	314	0,314
4	100	650	364	314	0,314
8	100	650	367	317	0,317
16	100	650	375	325	0,325
24	100	650	378	328	0,328
1	95	600	355	305	0,305
2	95	600	357	307	0,307
4	95	600	357	307	0,307
8	95	600	360	310	0,31
16	95	600	368	318	0,318
24	95	650	370	320	0,32
1	90	600	348	298	0,298
2	90	600	350	300	0,3
4	90	600	350	300	0,3
8	90	600	353	303	0,303
16	90	600	360	310	0,31
24	90	650	363	313	0,313
1	85	600	341	291	0,291
2	85	600	343	293	0,293
4	85	600	343	293	0,293
8	85	600	346	296	0,296

COMPUTER UTILIZATION TIME (HR)	CPU UTILIZATION (%)	UPS RATING (VA)	PSU WATTING (W)	POWER (W)	POWER (kW)
16	85	600	353	303	0,303
24	85	600	355	305	0,305
1	80	600	334	284	0,284
2	80	600	336	286	0,286
4	80	600	336	286	0,286
8	80	600	339	289	0,289
16	80	600	346	296	0,296
24	80	600	348	298	0,298
1	75	600	327	277	0,277
2	75	600	329	279	0,279
4	75	600	329	279	0,279
8	75	600	331	281	0,281
16	75	600	338	288	0,288
24	75	600	340	290	0,29
1	70	600	320	270	0,27
2	70	600	322	272	0,272
4	70	600	322	272	0,272
8	70	600	324	274	0,274
16	70	600	331	281	0,281
24	70	600	333	283	0,283
1	65	600	313	263	0,263
2	65	600	315	265	0,265
4	65	600	315	265	0,265
8	65	600	317	267	0,267
16	65	600	323	273	0,273
24	65	600	326	276	0,276
1	60	600	306	256	0,256
2	60	600	308	258	0,258
4	60	600	308	258	0,258
8	60	600	310	260	0,26
16	60	600	316	266	0,266
24	60	600	318	268	0,249
1	55	600	299	249	0,251
2	55	600	301	251	0,251

COMPUTER UTILIZATION TIME (HR)	CPU UTILIZATION (%)	UPS RATING (VA)	PSU WATTING (W)	POWER (W)	POWER (kW)
4	55	600	301	251	0,253
8	55	600	303	253	0,259
16	55	600	309	259	0,261
24	55	600	311	261	0,242
1	50	500	292	242	0,242
2	50	500	294	244	0,244
4	50	500	294	244	0,244
8	50	500	296	246	0,246
16	50	600	301	251	0,251
24	50	600	303	253	0,253

The mean of each category of data with the same utilization degree was calculated and the mean average power consumption of the server was derived.

Table 3: CPU Utilization Vs Power required

CPU UTILIZATION (%)	POWER (W)
100	318,333
95	311,167
90	304,000
85	296,833
80	289,833
75	282,333
70	275,333
65	268,167
60	261,000
55	254,000
50	246,667

Table 3 was used to plot a graph (see Figure 10) to get a linear relationship between power and CPU utilization rate and thus the formula was derived.:

$$P_{core\ i\text{-}9} = 1.432.U_{cpu}+175.08$$

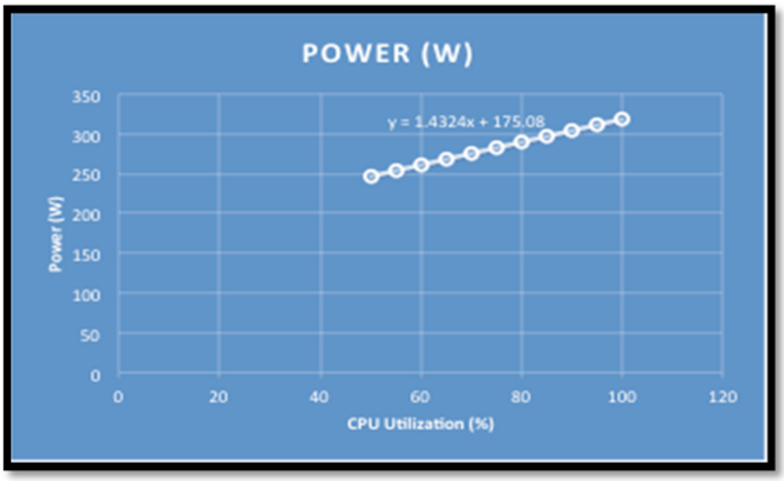


Figure 10: Power and CPU utilization linear relationship

3.3.1.1. GRID SOURCES AND CARBON EMISSION

To determine the CO_2 of electricity especially in this case the data center / server location is a big factor that influences the amount of emissions. The value varies from country to country and is a function of how energy is generated. The CO_2 that was used in this model is 0.26.

3.3.1.2. SERVER APPLICATION TYPE AND WORKLOAD DEFINITION

The application type deployed on a server used for monitoring vessels has been categorized based on data requirement; see Tables 4 and 5:

Table 4: Server application and workload

APPLICATION TYPE	REQUIREMENTS	CHARACTERISTICS	DATA REQUIREMENT
Batch processing application (Mapreduce)	High data storage Low user access High Hard disk utilization Low CPU utilization (on average)	Cluster dedicated to running massive batch jobs offline. Uses multiple nodes in parallel. Activity level not related to time of the day	Digital twin data stored can be used with historical data / near real time data (weather, traffic, and ship) to develop models.
Real-time application	High user access Medium data storage High CPU utilization High user access	Data handling of stream data, requires processing in real time, access to several data sources	Digital twin data Weather data is accessed in realtime Vessle Traffic also accessed inrealtime. Current data from ship is also accessed inreal time.
Combination of real-time and batch processing	High CPU utilisation High hard disk utilization High user access	Combination of batch and realtime	Combination of batch and realtime

Table 5: Server specification

COMPONENT TYPE	BLADE SERVER	ITANIUMSERVER	VCORE SERVER
CPU TYPE & SPEED	2.2 GHz AMD Turion	4x 1.5 Hz Itanium 2	3.3GHz Vcore 1.2 V
MEMORY	512MB SDRAM	1 GB	4 x 4GB DDR4 module FB DIMMS
STORAGE	40GB 2.5"Hard disk	36GB 3.5"Hard disk	4 Sata 7.2k RPM
NETWORK	10/100Mbit Ethernet	10/100Mbit Ethernet	10/100Mbit Ethernet

The Intel Core i9 server was used. Other studies show that CPU utilization is the main variable for machine – level activity of a server. (WSP Environment & Energy LLC, Natural Resources Defence Council, 2012). It varies based on the type and size of workload on the server. For instance, a web search requires high data processing and intensity varies in the time of the day. MapReduce (used for batch processing) requires multiple servers. The pattern of usage varies because it is not called in real-time, whilst webmail requires more disk I/O usage. (Fan, Weber, & Barroso, 2007)

To determine the CPU utilization to be used, an average of collected values is normally generated; however, Table 6 displays some extracted CPU utilization rates from the literature, which was used in each model deployment with two use case scenarios and accessed. Two scenarios were used because for each defined voyage the ships operation is monitored in three different modes. For container ships while at the port less monitoring is required, thus in the model design, the port is classified to the average case scenario.

Table 6: Server CPU utilization rates based on best practice to worst case

1. NON-VIRTUALIZED SERVER (IN-HOUSE / SERVER HOSTED EXTERNALLY		
CASE SCENARIO	SERVER CPU UTILIZATION	REFERENCE
Worst case	5%	WSP Environment & Energy LLC & Natural Resources Defence Council, 2012
Average case	10%	(Forrester Consulting, 2009) (Otto, 2010)
Best practice case	25%	(Cole, 2009)
2. VIRTUALIZED IN-HOUSE SERVER / PRIVATE CLOUD		
CASE SCENARIO	SERVER CPU UTILIZATION	REFERENCE
Worst case	6% In-house 7% Private cloud	(Kaplan, Forrest, & Kindler, 2008)
Average case	30%	WSP Environment & Energy LLC & Natural Resources Defence Council, 2012
Best practice case	60%	(Koomey, 2011) (VMware, 2018)
3. PUBLIC CLOUD		
CASE SCENARIO	SERVER CPU UTILIZATION	REFERENCE
Worst case	7%	(Liu, 2011)
Average case	40%	WSP Environment & Energy LLC & Natural Resources Defence Council, 2012
Best practice case	70%	(Koomey, 2011) (VMware, 2018)

Note: That based on PUE, energy for non-virtualised in-house is not equal to non-virtualized hosted externally, but for the purpose of the server energy consumption and scope they are categorized as same

3.3.2. SHIP OPERATION MODES

Ship operations are normally monitored during the 3 operating modes but at varying degrees. With respect to energy consumption of the server used for monitoring, high request is done mostly during the sailing and manoeuvring modes (depending on the ship type such as container vessels), thus workload on the servers at these times would be higher than at port time.

3.3.3. MODEL FOR ENERGY CONSUMPTION

The energy consumption model developed for server depends on the two scenarios and is defined below:

1. Energy consumption model for Server (non-virtualized) and Ship on a single voyage is:

   Server energy consumption1 **= $P_{core\ i\text{-}9}$ at Sea (25% U_{cpu}).t + $P_{core\ i\text{-}9}$ at Man (25% U_{cpu}).t + $P_{core\ i\text{-}9}$ at Port (10% U_{cpu}).t**

2. For a scenario where Virtualized servers are used for a fleet of Ships in a single voyage, the formula below was used to determine the server energy consumption.

   Server energy consumption2 =**$P_{core\ i\text{-}9}$ at Sea (70% U_{cpu}).t + $P_{core\ i\text{-}9}$ at Man (70% U_{cpu}).t + $P_{core\ i\text{-}9}$ at Port (40% U_{cpu}).t**

where t = time at sea, manoeuvring or at port for a voyage

While the energy consumption model for a Ship is defined below:

Ship energy consumption **= E_{Tfoc} at Sea + E_{Tfoc} at Man + E_{Tfoc} at Port**

where

$$E_{Tfoc} = \frac{E_{Hfoc} \times T}{1000} \text{ (tons)}$$

$$E_{Hfoc} = \frac{P_{eng} \times SFOC}{1000} \text{ (kg/H)}$$

where **E_{Hfoc} = Engine hourly fuel oil consumption**

P_{eng} = Engine power

SFOC = Specific fuel oil consumption

3.4. EMISSION MODEL

The emission model for server is calculated based on the grid carbon factor which differs from location based source of energy used.

The carbon factor used to calculate emissions from ships are defined by the IMO which is based on the type of fuel used for propulsion. Thus the server and ship emissions are defined below:

Server Emission = Server energy consumption**.** $\mathbf{C_{gf}}$
where $\mathbf{C_{gf}}$ **= Grid Carbon factor**

Ship Emission = $\mathbf{E_{Tfoc}}$ **at Sea .**$\mathbf{C_f}$ **+** $\mathbf{E_{Tfoc}}$ **at Man .** $\mathbf{C_f}$ **+** $\mathbf{E_{Tfoc}}$ **at Port .** $\mathbf{C_f}$
where $\mathbf{C_f}$ **= Carbon for fuel type used**

3.5. CHAPTER SUMMARY

In this chapter, the required information needed for development of the emission calculator was gathered. The sequence diagram was developed highlighting the actors and their roles. Ship static data source was identified - the EU TEFLES file, formulae to calculate the power consumed by two server types was extracted from a research paper and formula for an Intel core i-9 server was derived. Also the energy consumption model for a server used during a voyage by a ship was also derived. In the next chapter the process for development of the emission calculator is described.

CHAPTER 4: IMPLEMENTATION WITH JAVA PROGRAM

4.1. POWER / EMISSION CALCULATOR

Chapter 3 dealt with the requirements from data acquisition system to communication, storage and processing, identified 3 operational modes in ship operations, derived formula for the Core i9 server with defined specification, and dealt with the development of energy consumption and emission models. In this chapter, these models and formulae are used to develop the emission calculator.

Three major object oriented concepts used in this chapter are defined below:

1. **Objects**: An object in java is comprised of data and procedures. It has a state and behaviour. The state is stored in variables, while the behaviour is shown by functions or methods.
2. **Attributes**: Is an element that makes up a row in a database; they can also be referred to as a field.
3. **Class**: It defines the properties and behaviour of objects.

4.2. DESIGN, IMPLEMENTATION & TESTING

Based on the scope for the development of the emission calculator, which is limited to CO_2 emission, the formulae derived in conjunction with deeper analysis helped to determine the variables required and thus the following steps were carried out:

1. Create the database with DataGrip DBMS
2. Design the GUI
3. Script in java
4. Compile and execute

5. Populate the database with test data
6. Test and validate functions
7. Fix bugs
8. Re-factor program
9. Test and validate function

The scope of this application is limited to:

1. Three (3) modes of a ship in operation:
    a. Sailing mode: It is assumed that the ship is operating in stable mode, thus no change in engine parameter is noticed.
    b. Maneuvering mode: the mode of operation when approaching coastal area, entering or leaving port.
    c. Port mode
2. In this research, a voyage is assumed to be the distance from point of one sail to point at the port.
3. The server resource usage is known in advance

4.2.1. DATABASE SCHEMA

From the requirements gathered and analysis made, the two major objects identified were ship and server, thus the two Tables major "*the Ship*" and "*the Server*" were created. Other objects while other objects are required to achieve the objective of the software application. The 7 (seven) objects and their related attributes listed below were first created using sql statements:

1. tblship
2. tblmos
3. tblshipengine
4. tblfueltype
5. tblconsumpttype
6. tblserver
7. tblemission

See below sql statement used to create tblfueltype object:

```
create table tblfueltype
(
```

```
    id          int          not null
       primary key,
    fueltype         varchar(100)   null,
    carbonfactor  decimal(18, 2)  null
 );
```

The attribute ***"id"*** is defined as a primary key i.e. as a unique identifier and can be used to reference attributes by other objects.

$$E_{Hfoc} = \frac{P_{eng} \times SFOC}{1000}$$

where E_{Hfoc} = Engine hourly fuel oil consumption

P_{eng} = Engine power

SFOC = Specific fuel oil consumption

When an engine is used for a time T (in hours), the fuel consumption for the period T is:

$$E_{Tfoc} = \frac{E_{Hfoc} \times T}{1000}$$

Also noted from the analysis, the SFOC of a ship engine varies based on the fuel type, the engine manufacturer and the engine type. Each engine type has 3 fuel options; HFO, MDO and MGO and a ship uses a combination of one or more main engines, one or more auxiliary engines, and the boiler power during a voyage.

Moreover, during any operation mode (sailing, manoeuvring or at port) a minimum of two engine types are used to power the vessel. From studies conducted with the TEFLES excel file, mostly at sea mode, the main engine, auxiliary engine and boiler are used. From the ships listed, 8 of 20 ships run without the auxiliary engine during sea time.

At manoeuvring mode, the three types are used, while at port the auxiliary engine and boiler power are used.

Based on the above analysis, the ***tblshipengine*** object attributes were defined as seen below to enable it to hold parameters for each engine type used during a mode of operation:

Table attributes ***Character types /size***

enginetype	*varchar(5)*	*null*
engineno	*varchar(20)*	*null*
regulation	*decimal(18, 4)*	*null*
enginerpm	*decimal(18, 4)*	*null*
smaineenginerpm	*decimal(18, 4)*	*null*
smainenginepower	*decimal(18, 4)*	*null*
smainengsfoc	*decimal(18, 4)*	*null*
smaxspeed	*decimal(18, 4)*	*null*
sauxginerpm	*decimal(18, 4)*	*null*
sauxenginepower	*decimal(18, 4)*	*null*
sauxengsfoc	*decimal(18, 4)*	*null*
sauxmaxspeed	*decimal(18, 4)*	*null*
sboilersfoc	*decimal(18, 4)*	*null*
sboilerengpower	*decimal(18, 4)*	*null*
mvmenginerpm	*decimal(18, 4)*	*null*
mvmainenginepo	*decimal(18, 4)*	*null*
mvmainengsfoc	*decimal(18, 4)*	*null*
mvsmaxspeed	*decimal(18, 4)*	*null*
mvauxginerpm	*decimal(18, 4)*	*null*
mvauxenginepower	*decimal(18, 4)*	*null*
mvauxengsfoc	*decimal(18, 4)*	*null*
mvauxmaxspeed	*decimal(18, 4)*	*null*
mvboilersfoc	*decimal(18, 4)*	*null*
mvboilerengpower	*decimal(18, 4)*	*null*
bowthrusterpower	*decimal(18, 4)*	*null,*
bowthrusteropime	*decimal(18, 4)*	*null,*
winchpower	*decimal(18, 4)*	*null,*
winchoptime	*decimal(18, 4)*	*null,*
pmenginerpm	*decimal(18, 4)*	*null,*
pMAINENGPOWER	*decimal(18, 4)*	*null,*
pmainengsfoc	*decimal(18, 4)*	*null,*
pmmaxspeed	*decimal(18, 4)*	*null,*
pauxginerpm	*decimal(18, 4)*	*null,*
pauxenginepower	*decimal(18, 4)*	*null,*
pauxengsfoc	*decimal(18, 4)*	*null,*
pauxmaxspeed	*decimal(18, 4)*	*null,*
pboilersfoc	*decimal(18, 4)*	*null,*
pboilerengpower	*decimal(18, 4)*	*null,*
sailtime	*decimal(18, 4)*	*null*

Where "enginerpm " **is the attribute name**

"decimal (18, 4) " **is the character type** with **"18 "**specifying the maximum length and **"4"** the maximum decimal place of the attribute and "null" represents that the no value for that attribute has been entered.

Based on the 3 formulae below, *tblserver* attributes defined were servername, cpu, memory,storage and network to define specification of the 3 types of server.

$$P_{blade} = 14.45 + 0.236.\ U_{cpu} - (4.47E - 8).\ U_{mem} + 0.00281.\ U_{disk} + (3.1E - 8).\ U_{net}$$

$$P_{itanium} = 635.62 + 0.1108.\ U_{cpu} + (4.05E - 7).\ U_{mem} + 0.00405.\ U_{disk} + 0.\ U_{net}$$

$$P_{core\ i\text{-}9} = 1.432.U_{cpu} + 175.08$$

4.2.2. SOFTWARE IMPLEMENTATION

With the Netbeans IDE, the project called bc2emissions was created; by default, a source package and library folder is also created. In the source package, 18 classes were created. The first set of classes created were to mirror the tables created in the database; ship.java, mos.java, shipengine.java, fueltype.java, consumptype.java, server.java and emission.java. In these classes, the attributes created are those required in the application for in tblship. Ten attributes were created, while in class ship only seven variables were publicly declared, see Figure 11

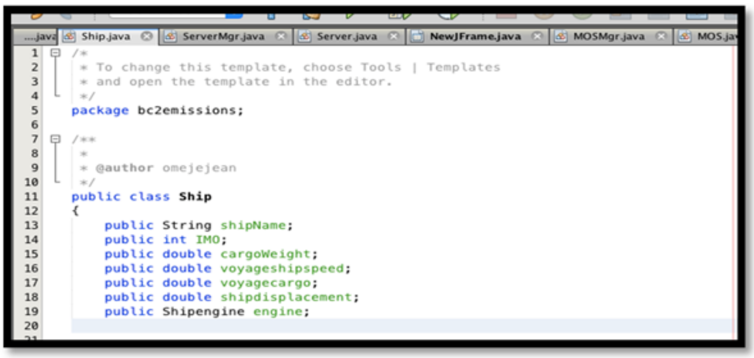


Figure 11: Class tblship

Other classes created are displayed in Figure 12.

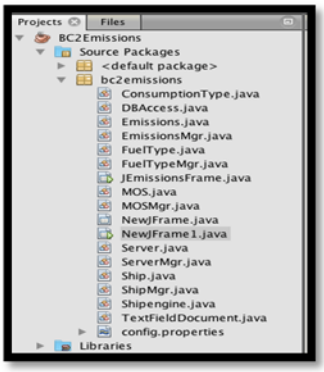


Figure 12: View of classes created

The two main classes, NewJFrame1.java and JEmissions.java provide an interface for the user and display the results. NewJFrame1 contains the code for all computations, while JEmissions holds GUI components that are used to display results. The code behind these frames retrieves and posts data to and from the dababase bc2emission. The NewJFrame1 class collects data from the required tables, computes and posts data to tblemission, while the JEmissions retrieves posted (computed) values from the tblemissions table and uses tblview to coordinate selected attributes from the tblemissions table for view by the user of the application. Figure 13 shows the emission form in design state while Figure 14 shows the form in executable state. Figure 15 is used to display the results of the emission calculation.

The GUI components used to develop a comprehensive user interface were frames, jbuttons, combobox, textfield, panels,l abels and jbuttons.
The two forms designed were NewJframe and JEmissionsFrame, which contains the main classes. For the design of the NewJFrame, panels, labels, textfields, combobox and jbuttons GUI components were used.:

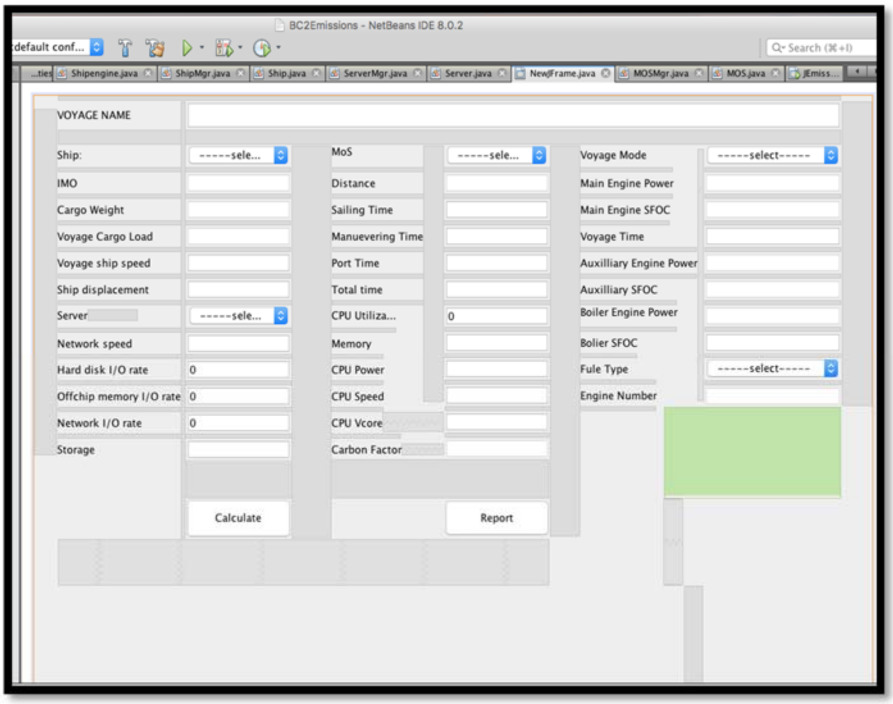


Figure 13: Emission form at design stage

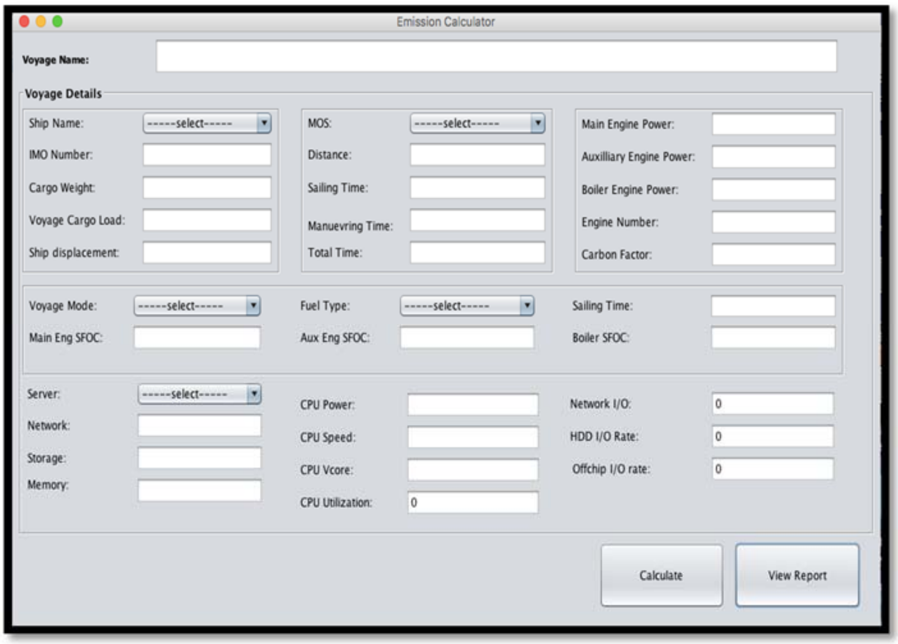


Figure 14: Emission form at run time

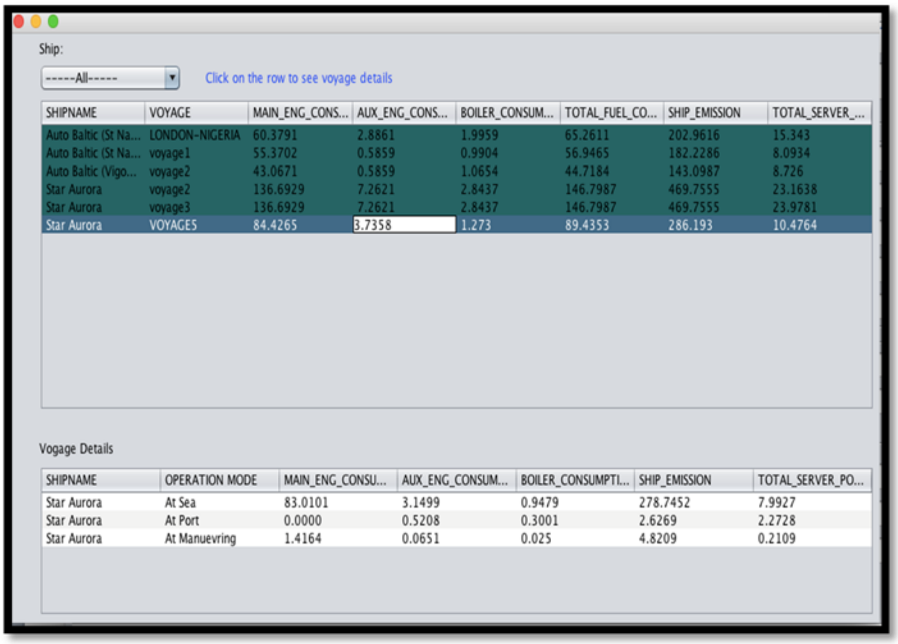


Figure 15: Detailed view of energy consumption and emissions

Based on the analysis and formulae, the major codes used for computation of fuel consumption, ship emission, computer power utilization and CO_2 emission are displayed in Figures 16 and 17:

```
        jcombofueltype.requestFocus();
        JOptionPane.showMessageDialog(null, "Pleass select a fuel type");
    }
    else if(selectedFMOS.equals("-----select-----"))
    {
        jcombomosname.requestFocus();
       JOptionPane.showMessageDialog(null, "Pleass select MOS");
    }

    else if(selectedServer.equals("-----select-----"))
    {
        jcomboservername.requestFocus();
        JOptionPane.showMessageDialog(null, "Pleass select a server");
    }
    else if (Time==0 || Time<0)
    {
       txttime.requestFocus();
       JOptionPane.showMessageDialog(null, "Pleass enter voyage time");
    }
    else
    {
       int fueltypeid=Integer.parseInt(lblfueltypeid.getText());
       int sailMode=FuelTypeMgr.getConsumptionType(selectedvoyageMode).Id;
       double Power=Double.parseDouble(txtserverpower.getText());

       double CO2=0;
       double carbonFactor=Double.parseDouble(txtcarbonfactor.getText());
       double voyagecargo=Double.parseDouble(txtvoyagecargoload.getText());
       double voyagespeed=Double.parseDouble(txtvoyagecargoload.getText());
       double cpu_utiliation=Double.parseDouble(txtcpuutilisation.getText());
       double hddrate=Double.parseDouble(txthddiorate.getText());

       double offchiprate=Double.parseDouble(txtoffchipmemiorate.getText());
       double enginepower=Double.parseDouble(txtmainenginepower.getText());
       double mainenginesfoc=Double.parseDouble(txtmainenginesfoc.getText());

       double auxenginepower=Double.parseDouble(txtauxengpower.getText());
       double auxenginesfoc=Double.parseDouble(txtauxenginesfoc.getText());
```

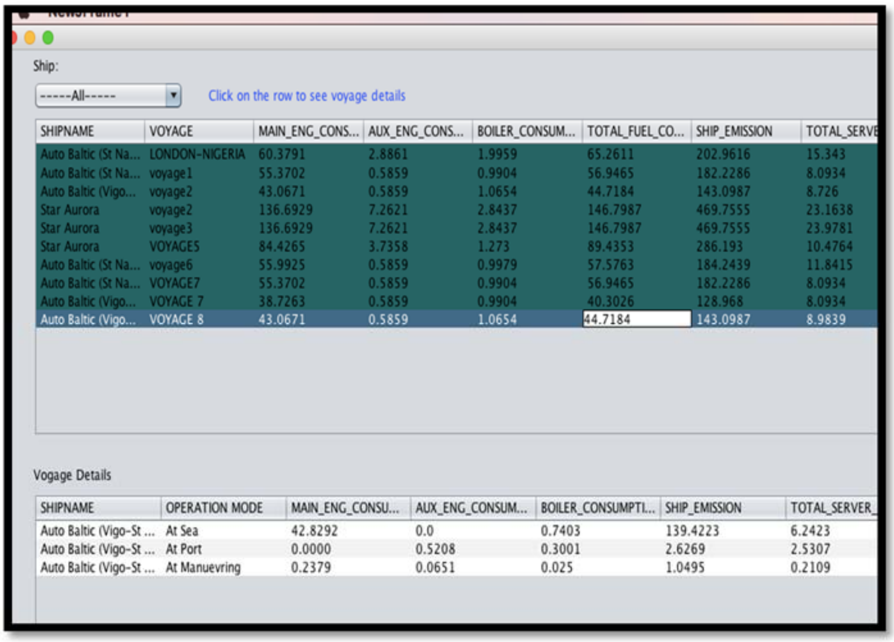
Figure 16: Script for calculating fuel consumption

```
emi.auxenginehfueloilconsumption=(auxenginepower*auxenginesfoc)/1000;
emi.auxtotalfuelconsumption=(emi.auxenginehfueloilconsumption*Time)/1000;
emi.auxengineSFOC=auxenginesfoc;
emi.auxemission= emi.auxtotalfuelconsumption*carbonFactor;

emi.boilerenginehfueloilconsumption=(boilerenginepower*boilersfoc)/1000;
emi.boilertotalfuelconsumption=(emi.boilerenginehfueloilconsumption*Time)/1000;
emi.boilerengineSFOC=boilersfoc;
emi.boileremission= emi.boilertotalfuelconsumption*carbonFactor;

emi.cpuutilization=cpu_utiliation;
emi.hddiorate= hddrate;
emi.offchipmemaccesscount=offchiprate;
emi.imono=Integer.parseInt(txtimo.getText());
emi.networkiorate=Double.parseDouble(txtnetworkiorate.getText());
emi.fueltype=Integer.parseInt(lblfueltypeid.getText());
emi.consumptiontype=Integer.parseInt(lblconsumptype.getText());
emi.sailMode=sailMode;
emi.voyageName=txtvoyagename.getText();
emi.dco2emission=((((1.4324*emi.cpuutilization)+175.08)*(Time))/1000);
emi.totalemission=(emi.sco2emission+emi.auxemission+emi.boileremission);


EmissionsMgr mgr=new EmissionsMgr();
if(mgr.saveShipEmission(emi)==true)
{
    JOptionPane.showMessageDialog(null, "Saved emission successfully");
}
else
{
    JOptionPane.showMessageDialog(null, "Unable to saved emission");
}

}


}
```

Figure 17: Script for calculating power consumption of server

4.2.3. TESTING AND RESULTS

The testing phase was carried out 23 times; it was a system level test with a short test script generated. The value for each operation mode's fuel consumption was tested against results from the EU TEFLES file to authenticate. The scope of testing was limited to the use of one fuel type (MDO) for all engine types used in all three modes. Fuel oil consumption of Ship 2 was calculated using MDO fuel type for all engines in all modes, with sailing time of 29.6 hours, manoeuvring time at 1 hour and port time at 12 hours. The total fuel consumption derived was 44.7148 tons. See Figures 18 and 19. The total fuel oil consumption derived from the TEFLES file for same test case gave 44.846tons.


Ship:

-----All-----

Click on the row to see voyage details

SHIPNAME	VOYAGE	MAIN_ENG_CONS...	AUX_ENG_CONS...	BOILER_CONSUM...	TOTAL_FUEL_CO...	SHIP_EMISSION	TOTAL_SERVE
Auto Baltic (St Na...	LONDON-NIGERIA	60.3791	2.8861	1.9959	65.2611	202.9616	15.343
Auto Baltic (St Na...	voyage1	55.3702	0.5859	0.9904	56.9465	182.2286	8.0934
Auto Baltic (Vigo...	voyage2	43.0671	0.5859	1.0654	44.7184	143.0987	8.726
Star Aurora	voyage2	136.6929	7.2621	2.8437	146.7987	469.7555	23.1638
Star Aurora	voyage3	136.6929	7.2621	2.8437	146.7987	469.7555	23.9781
Star Aurora	VOYAGE5	84.4265	3.7358	1.273	89.4353	286.193	10.4764
Auto Baltic (St Na...	voyage6	55.9925	0.5859	0.9979	57.5763	184.2439	11.8415
Auto Baltic (St Na...	VOYAGE7	55.3702	0.5859	0.9904	56.9465	182.2286	8.0934
Auto Baltic (Vigo...	VOYAGE 7	38.7263	0.5859	0.9904	40.3026	128.968	8.0934
Auto Baltic (Vigo...	VOYAGE 8	43.0671	0.5859	1.0654	44.7184	143.0987	8.9839

Vogage Details

SHIPNAME	OPERATION MODE	MAIN_ENG_CONSU...	AUX_ENG_CONSUM...	BOILER_CONSUMPTI...	SHIP_EMISSION	TOTAL_SERVER_
Auto Baltic (Vigo-St ...	At Sea	42.8292	0.0	0.7403	139.4223	6.2423
Auto Baltic (Vigo-St ...	At Port	0.0000	0.5208	0.3001	2.6269	2.5307
Auto Baltic (Vigo-St ...	At Manuevring	0.2379	0.0651	0.025	1.0495	0.2109

Figure 18: Test result for calculating fuel consumption

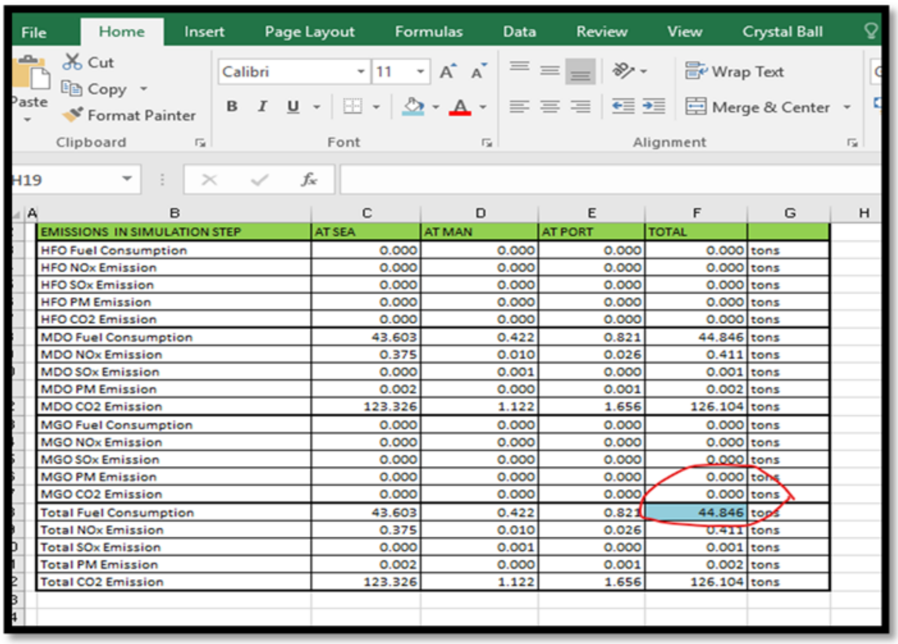

EMISSIONS IN SIMULATION STEP	AT SEA	AT MAN	AT PORT	TOTAL	
HFO Fuel Consumption	0.000	0.000	0.000	0.000	tons
HFO NOx Emission	0.000	0.000	0.000	0.000	tons
HFO SOx Emission	0.000	0.000	0.000	0.000	tons
HFO PM Emission	0.000	0.000	0.000	0.000	tons
HFO CO2 Emission	0.000	0.000	0.000	0.000	tons
MDO Fuel Consumption	43.603	0.422	0.821	44.846	tons
MDO NOx Emission	0.375	0.010	0.026	0.411	tons
MDO SOx Emission	0.000	0.001	0.000	0.001	tons
MDO PM Emission	0.002	0.000	0.001	0.002	tons
MDO CO2 Emission	123.326	1.122	1.656	126.104	tons
MGO Fuel Consumption	0.000	0.000	0.000	0.000	tons
MGO NOx Emission	0.000	0.000	0.000	0.000	tons
MGO SOx Emission	0.000	0.000	0.000	0.000	tons
MGO PM Emission	0.000	0.000	0.000	0.000	tons
MGO CO2 Emission	0.000	0.000	0.000	0.000	tons
Total Fuel Consumption	43.603	0.422	0.821	44.846	tons
Total NOx Emission	0.375	0.010	0.026	0.411	tons
Total SOx Emission	0.000	0.001	0.000	0.001	tons
Total PM Emission	0.002	0.000	0.001	0.002	tons
Total CO2 Emission	123.326	1.122	1.656	126.104	tons

Figure 19: Verification of test result using Crystalball and TEFLES file

Carbon factor for MDO 3.21 was used to determine the CO_2 emission in the Emission calculator program.

To validate the power consumption of the Server, the power is checked with the formula. if CPU utilization is 0%, 10% and 55% for all three servers was tested. Figure 20, 21 and 22 displays the results for all three servers when the CPU utilization is set at 0%.

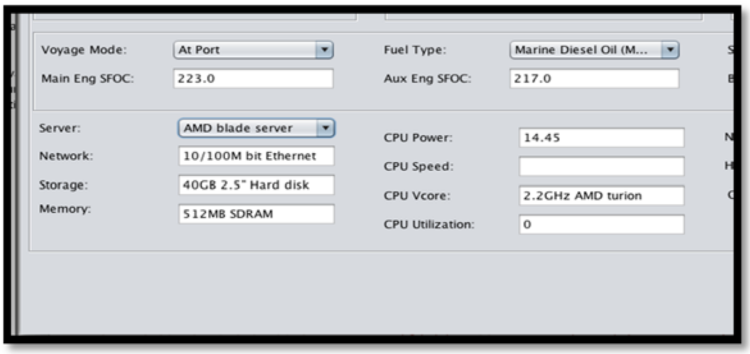


Figure 20: AMD blade server test screenshot

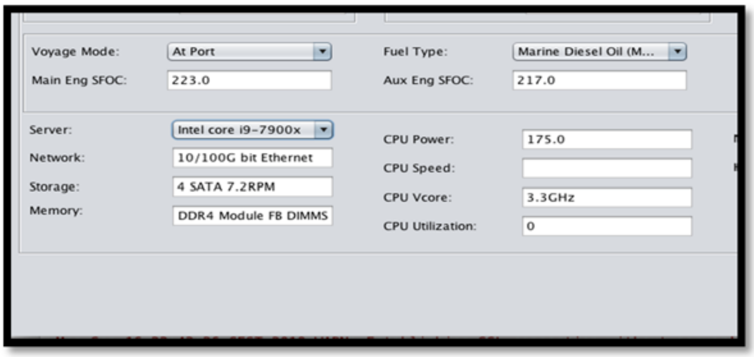


Figure 21: Intel core i9 server test screenshot

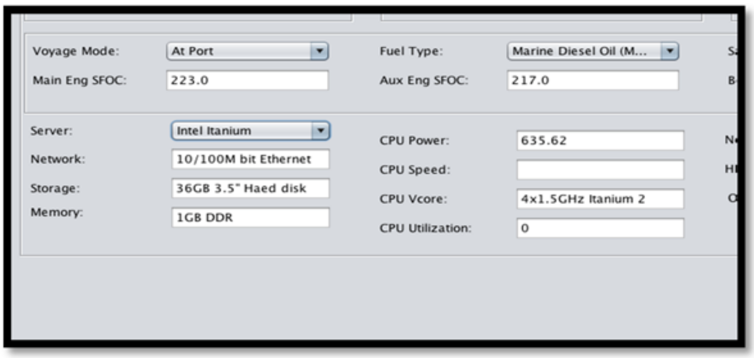


Figure 22: Itanium Server test screenshot

4.3. CHAPTER SUMMARY

The design, implementation and testing phases used for the development of the Emission calculator were described. The next chapter discusses in detail the results from these models.

CHAPTER 5: CASE STUDY

5.1. CASE STUDY ANALYSIS

The previous chapter discussed the development of the CO_2 emission calculator. In Chapter 5, the two models scenarios (non-virtualized and virtualized server) created in Chapter 3 were executed, final results were also discussed and analysed. Additionally, a new carbon emission intensity factor is applied and interesting results are discussed. The Two models were created, describing the application of varying CPU utilization at different modes of operation, and the power consumed by the Server during monitoring of the ship was displayed

5.2. MODEL DATA INPUT EXCLUSION, CONSTANTS AND VARIABLES

The following are exclusions for the models and scenarios:

1. Energy consumed during the life cycle of the development of the monitoring application.
1. Weather variance during the voyage (affect the voyage time and fuel consumption)
2. Hull maintenance and maintenance of other related capital equipment
3. Other data center computing devices, Racks, Power supply unit, UPS, Power Distribution System
4. Abatement technologies deployed by each vessel
5. Embedded energy of capital equipment and their energy use not directly related to servers and associated equipment.

Seven major criteria listed were kept constant:

1. MoS – Baltic MoS
2. Fuel type for all engines– MDO
3. Fuel type equivalent carbon factor - 3.21
4. Server type – Intel Core i9
5. Carbon factor -0.26
6. Maneuvering time – 1 hour
7. Port time – 12 hours

The server workload variable, CPU utilization varied for the three operating modes and also the sea time for each ship.

5.2.1. MODEL APPLICATION FOR A NON-VIRTUALIZED SERVER

The study quantified one application against 2 (two) deployment scenarios by multiplying the energy consumed by the Server CPU by the time taken to complete each operational mode.

The total fuel consumed by 20 ships was compared to the total energy for the Server. The CPU utilization rate is a factor that reflects the workload on the server. For the deployment scenario of a non-virtualized in-house server or server hosted externally, the CPU utilization during the 3 ship operating modes was considered and the best case assumed to be:

Table 7: Server CPU utilization rate per mode of operation for scenario 1

1. NON-VIRTUALIZED SERVER (IN-HOUSE \ HOSTED EXTERNALLY)	
SHIP OPERATION MODE	SERVER CPU UTILIZATION
Sailing	25%
Maneuvering	25%
Berth /Port	10%

The sailing time for the Baltic MoS is displayed in Table 8, while the manoeuvring time of 1 hour and Port time of 12 hours are constant for all ships. These values were extracted from the TEFLES file. The carbon conversion factor used for Server Power for the voyage is 0.26

Table 8: Ships sailing time for the Baltic Sea MoS

S/N	SHIP NAME	BALTIC SEA TIME FOR SAILING (H)
1	Auto Baltic (St Nazire-Vigo)	29,6
2	Auto Baltic (Vigo-St Nazire)	26,6
3	Star Aurora	37,9
4	Overseas Joyce	26,5
5	Cap San Nicolas	44,2
6	Coral Leader	32,1
7	Viking Chance	32,1
8	Morning Mead	25,2
9	Viking Drive	34,2
10	Autoprimer	40,8
11	Magnee Cours Express	33,1
12	MV Spica Leader	35,8
13	Bouzas	30,5
14	Galicia	39,9
15	L'Audace	30,3
16	Suar Vigo	29
17	Tenerife Car	30,3
18	Grand Canaria Car	37,9
19	Emerald Leader	34,2
20	TEST SHIP	34,2

Based on the defined input specification, the fuel consumption by each ship and the corresponding power consumed by each server are displayed in the Table 9. The Table provides the fuel consumed at various modes by the different engines and gives the sum total considering the number of hours for each mode.

Table 9: Ship -Server Energy Consumption and emissions for a voyage

	SHIP NAME	FUEL CONSUMPTION AT MSEA (TONS)	FUEL CONSUMPTION AT AUXSEA (TONS)	FUEL CONSUMPTION AT BOSEA	FUEL CONSUMPTION AT MMAN (TONS)	FUEL CONSUMPTION AT AUXMAN (TONS)	FUEL CONSUMPTION AT BOMAN	FUEL CONSUMPTION AT MPORT (TONS)	FUEL CONSUMPTION AT AUXPORT(TONS)	FUEL CONSUMPTION AT BOPORT	TOTAL SEA	TOTAL MAN	TOTAL PORT	TOTAL FUEL CONP (tons)	TOTAL FUEL CONP (kWH)	TOTAL CO2 EMISSION (kgCO2)	SERVER POWER CONSUMPTION AT SEA (kW)	SERVER POWER CONSUMPTION AT MAN	SERVER POWER CONSUMPTION AT PORT	TOTAL SERVER POWER FOR VOYAGE (kWH)
1	Auto Baltic (St Nazire-Vigo)	61,4129096	0	0,7403	0,195627	0,0651	0,025	0	0,5208	0,3001	62,15	0,2857	0,82092	63,2598623	73521,8771	202,4315593	6,242344	0,21089	2,272848	8,726082
2	Auto Baltic (Vigo-St Nazire)	38,4882392	0	0,66527	0,237848	0,0651	0,025	0	0,5208	0,3001	39,15	0,328	0,82092	40,3023835	46840,2361	129,370651	5,609674	0,21089	2,272848	8,093412
3	Star Aurora	83,010096	3,14991	0,94788	1,416425	0,0651	0,025	0	0,5208	0,3001	87,11	1,5065	0,82092	89,4353369	103943,537	286,193078	7,992731	0,21089	2,272848	10,476469
4	Overseas Joyce	70,8589789	2,20259	0,66277	0,340541	0,0651	0,025	0	0,5208	0,3001	73,72	0,4307	0,82092	74,9759026	87138,4935	239,9228883	5,588585	0,21089	2,272848	8,072323
5	Cap San Nicolas	26,3709783	3,67351	1,10544	0,342895	0,0651	0,025	0	0,5208	0,3001	31,15	0,433	0,82092	32,4038518	37660,4046	103,6923256	9,321338	0,21089	2,272848	11,805076
6	Coral Leader	33,1952993	2,66786	0,80282	0,270579	0,0651	0,025	0	0,5208	0,3001	36,67	0,3607	0,82092	37,847592	43987,2284	121,1122945	6,769569	0,21089	2,272848	9,253307
7	Viking Chance	31,0843447	2,66786	0,80282	0,277349	0,0651	0,025	0	0,5208	0,3001	34,56	0,3675	0,82092	35,743408	41541,7036	114,3789054	6,769569	0,21089	2,272848	9,253307
8	Morning Mead	76,2588327	2,0944	0,63025	0,376629	0,0651	0,025	0	0,5208	0,3001	78,98	0,4667	0,82092	80,2711407	93292,7251	256,8676502	5,314428	0,21089	2,272848	7,798166
9	Viking Drive	27,5454709	2,8424	0,85534	0,257278	0,0651	0,025	0	0,5208	0,3001	31,24	0,3474	0,82092	32,4115173	37669,3136	103,7168552	7,212438	0,21089	2,272848	9,696176
10	Autoprimer	17,3884837	3,39093	1,02041	0,186304	0,0651	0,025	0	0,5208	0,3001	21,8	0,2764	0,82092	22,8971545	26611,5309	73,27089441	8,604312	0,21089	2,272848	11,08805
11	Magnee Cours Express	31,7292941	2,75097	0,82783	0,318522	0,0651	0,025	0	0,5208	0,3001	35,31	0,4086	0,82092	36,5376516	42464,7894	116,920485	6,980459	0,21089	2,272848	9,464197
12	MV Spica Leader	26,3201572	2,97537	0,89536	0,320501	0,0651	0,025	0	0,5208	0,3001	30,19	0,4106	0,82092	31,4224201	36519,7651	100,5517443	7,549862	0,21089	2,272848	10,0336
13	Bouzas	41,249214	0	0,76281	0,212021	0,0651	0,025	0	0,5208	0,3001	42,01	0,3021	0,82092	43,1350701	50132,4411	138,0322242	6,432145	0,21089	2,272848	8,915883
14	Galicia	22,5860934	0	0,9979	0,179205	0,0651	0,025	0	0,5208	0,3001	23,58	0,2693	0,82092	24,6742275	28676,8806	78,95752785	8,414511	0,21089	2,272848	10,898249
15	L'Audace	41,5169264	0	0,7578	0,212093	0,0651	0,025	0	0,5208	0,3001	42,27	0,3022	0,82092	43,3978521	50437,8517	138,8731269	6,389967	0,21089	2,272848	8,873705
16	Suar Vigo	45,0059141	0	0,72529	0,216322	0,0651	0,025	0	0,5208	0,3001	45,73	0,3064	0,82092	46,8585564	54459,9514	149,9473806	6,11581	0,21089	2,272848	8,599548
17	Tenerife Car	40,7165456	0	0,7578	0,17201	0,0651	0,025	0	0,5208	0,3001	41,47	0,2621	0,82092	42,5573881	49461,0476	136,183642	6,389967	0,21089	2,272848	8,873705
18	Grand Canaria Car	24,3331322	0	0,94788	0,153074	0,0651	0,025	0	0,5208	0,3001	25,28	0,2432	0,82092	26,3451156	30618,8203	84,30437005	7,992731	0,21089	2,272848	10,476469
19	Emerald Leader	32,5714233	2,8424	0,85534	0,319632	0,0651	0,025	0	0,5208	0,3001	36,27	0,4097	0,82092	37,4998235	43583,0449	119,9994353	7,212438	0,21089	2,272848	9,696176
20	TEST SHIP	32,5716884	2,8424	0,85534	0,319632	0,0651	0,025	0	0,5208	0,3001	36,27	0,4097	0,82092	37,5000886	43583,353	120,0002836	7,212438	0,21089	2,272848	9,696176
														879,476343	**978561,642**	**2814,727322**				**189,79008**

Table 10 compares the server power consumed during the voyage to the total fuel consumed for that voyage.

Table 9: Ship to Server energy consumption

S/N	SHIP NAME	TOTAL FUEL CONP (kWH)	TOTAL SERVER POWER FOR VOYAGE (kWH)
1	Auto Baltic (St Nazire-Vigo)	73521,88	8,73
2	Auto Baltic (Vigo-St Nazire)	46840,24	8,09
3	Star Aurora	103943,54	10,48
4	Overseas Joyce	87138,49	8,07
5	Cap San Nicolas	37660,40	11,81
6	Coral Leader	43987,23	9,25
7	Viking Chance	41541,70	9,25
8	Morning Mead	93292,73	7,80
9	Viking Drive	37669,31	9,70
10	Autoprimer	26611,53	11,09
11	Magnee Cours Express	42464,79	9,46
12	MV Spica Leader	36519,77	10,03
13	Bouzas	50132,44	8,92
14	Galicia	28676,88	10,90
15	L'Audace	50437,85	8,87
16	Suar Vigo	54459,95	8,60
17	Tenerife Car	49461,05	8,87
18	Grand Canaria Car	30618,82	10,48
19	Emerald Leader	43583,04	9,70
20	TEST SHIP	43583,35	9,70
	TOTAL	**978561,64**	**189,79**

To understand the relationship between the energy consumed by the server and ship for that voyage, a graph was plotted; see Figure 23.

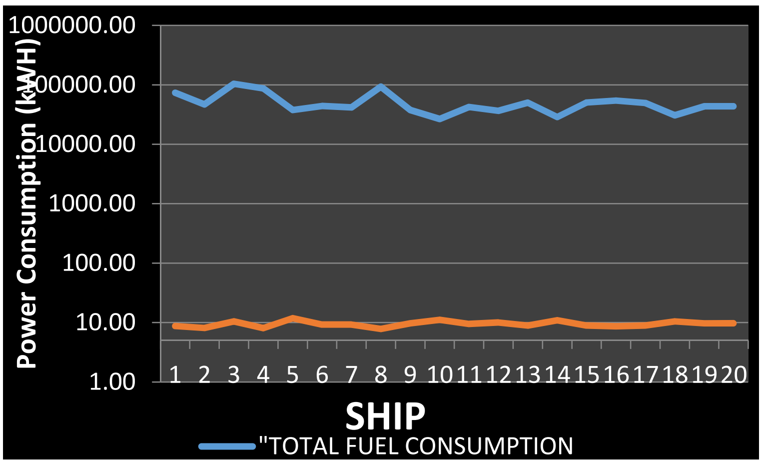


Figure 23: Ship fuel Vs Server CPU power consumption

Table 11 compares the direct and indirect emissions of 20 ships by the use of big data analytical applications but limited to the server power consumption.

Table 10: Ship - Server emission for Model scenario for non-virtualized server

S/N	SHIP NAME	TOTAL CO2 EMISSION (kgCO2)	SERVER EQU CO2e EMISSION (kgCO2)	SERVER TO SHIP EMMISSION %
1	Auto Baltic (St Nazire-Vigo)	202,43	2,27	1,12076
2	Auto Baltic (Vigo-St Nazire)	128,97	2,10	1,63164
3	Star Aurora	286,19	2,72	0,95176
4	Overseas Joyce	239,92	2,10	0,87478
5	Cap San Nicolas	103,69	3,07	2,96003
6	Coral Leader	121,11	2,41	1,98647
7	Viking Chance	114,38	2,41	2,10341
8	Morning Mead	256,87	2,03	0,78933
9	Viking Drive	103,72	2,52	2,43066
10	Autoprimer	73,27	2,88	3,93457
11	Magnee Cours Express	116,92	2,46	2,10459
12	MV Spica Leader	100,55	2,61	2,59442
13	Bouzas	138,03	2,32	1,67941
14	Galicia	78,96	2,83	3,58869
15	L'Audace	138,87	2,31	1,66135
16	Suar Vigo	149,95	2,24	1,49111
17	Tenerife Car	136,18	2,31	1,69416
18	Grand Canaria Car	84,30	2,72	3,23101
19	Emerald Leader	120,00	2,52	2,10085
20	TEST SHIP	120,00	2,52	2,10083
	TOTAL	**2 814,32**	**49,35**	**1,75337**

5.2.1.1. NON-VIRTUALIZED SERVER MODEL EVALUATION

For each ship, 21 events occurred during implementation. Thus, a total of 420 events represents the data set produced; 410 events were used for model fitting, while 10 events (2.38% equivalent) were used for validation of the dataset.

The general observation from Figure 23 shows that the relationship between ship fuel consumption and server power consumption for a voyage are not linear in nature; thus, it creates an avenue for optimization.

As seen in Table 9 and Figure 23, Ship 3 consumed the highest quantity of fuel during the voyage on the Baltic MoS route, 89.44 tons of fuel and server power consumption of 10.48kWh, while Ship 18 used 84.30 tons of fuel and server power consumption was also 10.48kWh. The server used for both Ships 3 and 18 were similar because the time taken to complete a voyage was the same. To substantiate this point, Ship 8 used 80.27tons of fuel and server power of 7.80kWh (the least server power) for the same trip.

Since the time of a voyage affects the power consumption of the server, Ship 5 had the highest indirect emission (server emission) 3.07kgCO_2. One known measure for fuel reduction in ship operation is slow steaming. This implies that if a ship owner monitors vessels with real–time big data applications, slow steaming may have an effect on server consumption and by extension increase emissions indirectly (passed to data centers). If the time is reduced to decrease the indirect emissions, due to the speed time relationship, it implies that the speed would increase, more fuel consumed and direct emission would increase. In this case, the application of trade-off principle is applied.

The results also imply that the size of the ship and engine power do not directly influence the power consumption of a server in a data center. Rather the type of business applications accessed (which determines the workload) is one important factor. The best method to reduce emission is thus to subscribe to vendors that provide SaaS; thus, the ship operator uses and pays only when the service is used on a voyage.

5.2.2. MODEL APPLICATION FOR A VIRTUALIZED SERVER

In this scenario, the total energy consumed for a fleet of 20 ships is compared with energy for total energy to power a virtualized server. Virtualization requires fewer physical servers, thus we have one physical server and other virtual servers depending on the virtualization ratio. The ratio used in this model is 5:1, which implies a fleet of 5 ships are grouped to access ship operation monitoring tools from 1 physical server. With a mix of workload consolidation and CPU voltage and frequency scaling (DVS), the CPU utilization was assumed to be at 70% maximum at sea and manoeuvring while at port the CPU utilization is 40%.

Table 12: Sever CPU utilization rate per mode of operation for Model scenario 2

2. VIRTUALIZED IN-HOUSE SERVER / CLOUD	
SHIP OPERATION MODE	**SERVER CPU UTILIZATION**
Sailing	70%
Maneuvering	70%
Berth /Port	40%

5.2.1.2. VIRTUALIZED MODEL EVALUATION

Table 13 shows a breakdown of the consumption of the virtualized server running at a ratio of 5:1. This implies that five ships share one physical server for the real-time monitoring of the ships in operation, but each has its own virtual server. The CPU utilization increased because the workload increased by five. This optimized the server CPU utilization rate to a large extent when compared to one ship using a single server for monitoring. Forrester Consulting (2009), Otto (2010) and Kaplan, Forrest, & Kindler (2008) observed that in an average case the CPU utilization of a server ranges from 6 -10 %.

Thus, the workload increase maximizes CPU utilization rate and also the power consumed to power the server.

Table 13: Server power consumption and CO2 emission for a virtualized environment

SHIP NAME	SERVER POWER CONSUMPTION AT SEA	SERVER POWER CONSUMPTION AT MAN	SERVER POWER CONSUMPTION AT PORT	TOTAL SERVER POWER FOR VOYAGE (kWH)	SERVER EQU CO2e EMISSION (kgCO2)
SERVER 1: Cap San Nicolas Auto Baltic (Vigo-St Nazire) Star Aurora Overseas Joyce Auto Baltic (St Nazire-Vigo)	12,17	0,28	2,79	15,23	3.96
SERVER 2: Coral Leader Viking Chance Morning Mead Viking Drive Autoprimer	11,23	0,28	2,79	14,30	3.72
SERVER 3: Magnee Cours Express MV Spica Leader Bouzas Galicia L'Audace	10,99	0,28	2,79	14,05	3.65
SERVER 4: Suar Vigo Tenerife Car Grand Canaria Car Emerald Leader TEST SHIP	10,44	0,28	2,79	13,50	3.51
	TOTAL			57,08	14,84

This model was designed with one additional assumption, that all vessels within the selected time (the largest time amongst the set) would access their applications and complete a voyage.

In this model, each ship's operation application is not located on individual physical servers. A virtualization ratio of 5:1 was used and there was a great decrease in the power consumed by the server and its related emissions. Servers 1 – 5 indirect emissions produced by a fleet of 20 ships were 14.84kgCO_2 when server power consumption at maximum sea time of 44.21hours was 57.08kWh.

Whilst the fuel consumption and equivalent emission of the 20 ships (the fleet) remain the same for both models, there was a huge reduction (69.92%) in server power consumption and its corresponding emissions when the 2 Models were compared; see Figure 24.

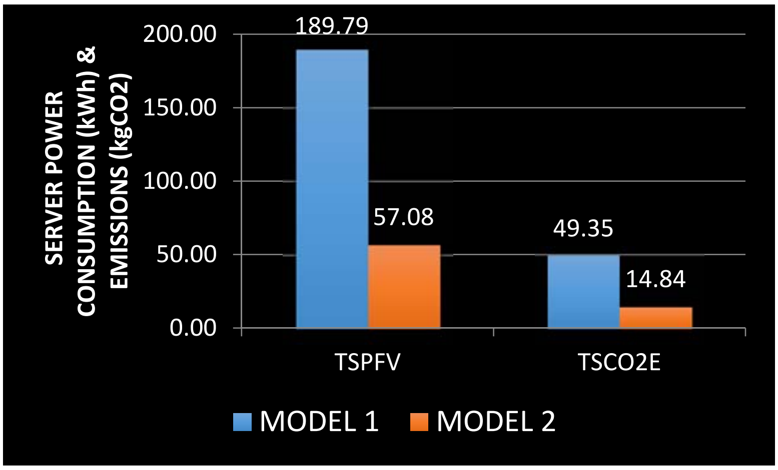


Figure 24: Comparison of Model scenarios 1 and 2

TSPFV: Total server power consumption for a voyage

TSCO2E: Total server CO_2 emission

MODEL 1: Non-virtualized server scenario
MODEL 2: Virtualized server scenario

Thus, adopting model scenario 2 can optimize the server power of a fleet, where a fleet of 10 ships can use one virtual server (with virtualization ratio of 10:1) to reduce the indirect emissions from using big data analytics application, or any real-time application required for ship operation.

5.2.3. CARBON FACTOR IMPACT

One major criteria that brings the best improvements in the emissions is the location of the server (data center). The location is based on the source of electrical energy; the energy source influences the amount of emissions a great deal. Sweden's carbon emission intensity was 0.013 as published in the European Environmental Agency for 2016; applying this value to both model scenarios, the results gave a tremendous reduction on emissions from the server; see Figure 25:

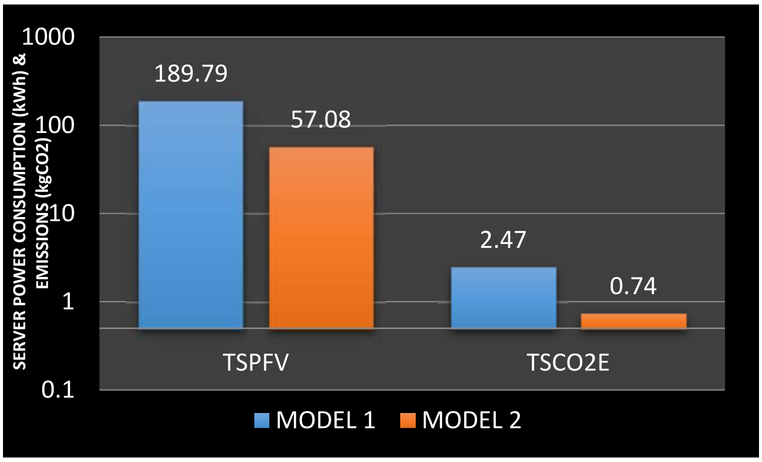


Figure 25: Comparison of Models 1 and 2 after new carbon factor is applied

From the Figure 26, there is an additional 1.75% (49.35kg) of CO_2 emitted indirectly by the total 20 ships, which is their corresponding server emission. Applying the carbon factor of 0.013 to model 1 (Figures 27 and 29) shows a 95% reduction of CO_2 emitted by the server. This is possible if all the individual servers for the 20 ships are located in Sweden and the carbon intensity of 0.013 is constant. Thus, the emission would decrease from 49.35kg CO_2 to 2.47kg CO_2. Whilst on application to Model 2, it would decrease from 14.34kg CO_2 to 0.74kg CO_2.

Figure 26: Model 1- Ship Vs Server power consumption and emission

TEC: Total energy consumption
TECO2E: Total CO2 emission

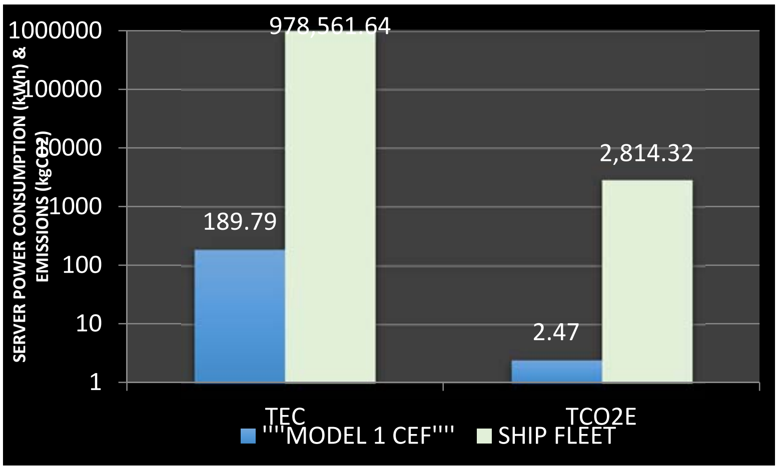


Figure 27: Model 1- Ship Vs Server power consumption and emission result with new CF applied

Figure 28: Model 2 – Servers Vs Fleet power consumption and emissions

Figure 29: Model 2- Ship Vs Server power consumption and emissions with new CF applied

5.3. CHAPTER SUMMARY

The above analysis estimates a 1.75% increase in indirect emissions (caused by the server) compared to the total ship emissions from a total of 20 ships involved in SSS in the Baltic MoS for only **one** voyage for Model 1. The emission rate depends on the workload, the server type, and the carbon factor. Model 2, due to same factors including virtualization, resulted in a 0.53% increase in emissions as compared to ship emissions, a 70% decrease compared to server emissions in Model 1.

When a carbon factor of 0.003 was applied to both, Model 1 produced about 0.087% additional emissions compared to ship emissions. For Model 2, it produced 0.026% compared to ship emissions for the fleet of 20 ships.

CHAPTER 6: CONCLUSION AND FURTHER RESEARCH

6.1. CONCLUSION

The first technological revolution in shipping started in 1800 where ship propulsion migrated from sail to mechanized power and the use of steam engines. This was followed by the introduction of electric power and internal combustion engines and next the introduction of computerized control systems in the 1970's. The third industrial revolution allowed all important engine control functions to be operated from the bridge and thus transformed ship operations radically.

Shipping 4.0, which is currently a hot topic in the maritime sector, is characterised by certain technologies - cyber physical system, IoT, and big data analytics to mention a few. While the benefits abound, the speed of migration is already limited by the readiness gap exhibited by countries and regions in the maritime sector due to their different priorities.

Big data technology, one of the concepts of the 4IR and Shipping 4.0, is very important to other concepts; the CPS, augmented reality, Internet of things at sea, simulation, optimization, AI, 3D printing, robotics and autonomy, which all rely on data. The processing of big data requires special data processing and high computing resources especially when accessed in real–time. The shipping sector has already adopted some of its applications especially in optimizing ship operations.

This research examined the quantity of emissions generated by ships in operation while using real-time processing applications to optimize performance. Three model scenarios were applied to optimize power consumption of the servers used for storage and processing of ship data transmitted. The aim was to quantify the amount of GHG emitted by the use of such telemetry services and establish measures to reduce indirect emission from Ship operations towards Shipping 4.0.

The investigation has been possible with the use of quantitative data sampled from the EU funded TEFLES project, which constitutes data from 20 ships with engine parameters for the main engine, auxiliary engine, shaft and boilers used during ship operation.
This data source was very useful as it considered several factors such as hull maintenance, after treatment, routes in the Motorway of the seas and so on.

Another useful source of information was derived from the literature; Economou et al (2006) utilized the Mantis model to derive formulae for a blade server and an Itanium server. After proper review of the formulae, it was established that the central processing unit (CPU) utilization rate was the most significant variable to determine the power consumption of a server. Thus, to derive a power formula for an intel Core i9- 7900 server, data extraction and statistical analysis was used to develop the formula employed in this research.
For the Server, the level of workload on the CPU at sea affects power consumption, which is always high, same at port. For a Container ship, server power consumed when at port was estimated to be lower than that at sea because port activities for such vessels require less monitoring. The workload is characterised by the CPU utilization.

For a ship in operation, the three modes were considered, sailing, manoeuvring and port mode. The ship energy model considered the various engines used in these 3 modes. Extracts from the data set of 20 ships show that 60% operate with main, auxiliary engines and boilers during sea time. At manoeuvring, mainly the auxiliary engines and boilers are used while at port boiler and auxiliary engine are used. For ship fuel consumption, the formula used to calculate the fuel consumption of each engine is based on the fuel type and the SFOC defined by the engine manufacturer. The server power is based on the CPU utilization, which is normally determined after several measurements of the amount of workload and transactions carried out by the server.

Noting the above, two main models, the model for energy consumption and the model for emissions calculation were developed.

The first model was implemented with data from 20 ships in the EU TEFLES project file. The maximum voyage time applied was 44.5 hours and the results showed that for the 20 ships only 0.019% of additional power was consumed by using real-time applications for ship operations and a 1.75% increase of CO_2 additional emissions was realised. When the model was implemented for virtualized servers for a fleet, more reductions in power consumption and emissions were realised.

Generally, it was observed that ship fuel consumption and server power consumption for a voyage are not linear. Moreover, the server power does not depend on the size of the ship and engine power of a ship rather it is time dependent. The best method to reduce emissions by using real-time application is to subscribe to vendors that provide Software as a Service (SaaS); thus, the ship operator pays only when the service is used on a voyage.

With the information gathered, a tool was developed using Netbeans IDE 8.0.2, DataGrip 2019 2.3 database management system (DBMS) and java-programming language to calculate the power consumption and corresponding emissions of a ship and the server used for real-time big data analytics during a voyage.

Towards Shipping 4.0, it has been demonstrated that with adequate implementation of a mixture of measures from the data center providers, there would be little fear of the amount of additional emissions the sector would contribute compared to the value produced.

This currently shows that the value derived from real-time processing outweighs the negative externality. Currently, different measures exist to drastically reduce the emission rate, but going by the rate of increase in data and its utilization, the amount of energy used for its processing needs, in future, needs to be re-evaluated and monitored.

6.2. LIMITATIONS

The greatest limitation encountered during this research was companies approached did not provide access to data or assistance.

6.3. FUTURE RESEARCH

With the exponential growth anticipated in IoT's, CPS and big data technologies, there is need for continuous monitoring to ensure that GHG emissions contributed are kept in check.

One area that requires further research is the full estimation of data centers as a whole; this research was limited to only the server. Although the location of a server or data center, implementation of cloud computing and also development of Hyper scale data centers are said to be more energy efficient, other significant energy uses such as the cooling system which uses about 28% of power compared to the server (Zhu, Zhu, & Agrawal, 2012) and rack system needs further research.

Data center facilities may lack on-line power monitoring and data collection systems that could be used to study power provisioning. This also requires more research.

With regard to the shipping sector, the need to utilize energy bills generated from the use of weather reports, access to vessel traffic services, onshore computing facilities and satellite communication devices needs to be conducted to evaluate the emissions produced. Also a full life cycle analysis of the use of big data from the point of development of the tools, programming the applications, installation of fibre optic channels (communication channels) until the end of life needs to be conducted.

The role of the shipping sector may also digress a little, as the issue of secret data theft, cyber- crimes, denial of service (DoS) may increase exponentially and the need to develop and control its own data would be paramount.

The Shipping sector could also earmark and gain extra points indicating that it has gone the extra mile to reduce emissions by ensuring that ship operations comply with several measures to reduce emissions through the use of big data analytics applications.

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