Master's degree thesis

LOG950 Logistics

Prioritization of effective variables in the smart marine fleet for short-distance voyages in order to improve managerial and competitive performance

Sharon Berg and Farhad Nourafshan

Number of pages including this page: 140

Molde, 22.05.2023

Molde University College
Specialized University in Logistics

Mandatory statement

Each student is responsible for complying with rules and regulations that relate to examinations and to academic work in general. The purpose of the mandatory statement is to make students aware of their responsibility and the consequences of cheating. Failure to complete the statement does not excuse students from their responsibility.

*Please complete the mandatory statement by placing a mark **in each box** for statements 1-6 below.*		
1.	**I/we herby declare that my/our paper/assignment is my/our own work, and that I/we have not used other sources or received other help than is mentioned in the paper/assignment.**	☒
2.	**I/we herby declare that this paper** • Has not been used in any other exam at another department/university/university college • Is not referring to the work of others without acknowledgement • Is not referring to my/our previous work without acknowledgement • Has acknowledged all sources of literature in the text and in the list of references • Is not a copy, duplicate or transcript of other work	☒
3.	**I am/we are aware that any breach of the above will be considered as cheating, and may result in annulment of the examinaion and exclusion from all universities and university colleges in Norway for up to one year, according to the Act relating to Norwegian Universities and University Colleges, section 4-7 and 4-8 and Examination regulations section 14 and 15.**	☒
4.	**I am/we are aware that all papers/assignments may be checked for plagiarism by a software assisted plagiarism check**	☒
5.	**I am/we are aware that Molde University college will handle all cases of suspected cheating according to prevailing guidelines.**	☒
6.	**I/we are aware of the University College`s rules and regulation for using sources**	☒

Personal protection

Personal Data Act

Research projects that processes personal data according to Personal Data Act, should be notified to Sikt for consideration.

Have the research project been considered by Sikt? ☐**yes** ☒**no**

- If yes:

Reference number:

- If no:

I/we hereby declare that the thesis does not contain personal data according to Personal Data Act.: ☐

Act on Medical and Health Research

If the research project is effected by the regulations decided in Act on Medical and Health Research (the Health Research Act), it must be approved in advance by the Regional Committee for Medical and Health Research Ethic (REK) in your region.

Has the research project been considered by REK? ☐**yes** ☒**no**

- If yes:

Reference number:

Publication agreement

ECTS credits: 30

Supervisor: Steinar Westlie Kristofferson

Agreement on electronic publication of master thesis

Author(s) have copyright to the thesis, including the exclusive right to publish the document (The Copyright Act §2).

All theses fulfilling the requirements will be registered and published in Brage HiM, with the approval of the author(s).

Theses with a confidentiality agreement will not be published.

I/we hereby give Molde University College the right to, free of charge, make the thesis available for electronic publication: ☒**yes** ☐**no**

Is there an agreement of confidentiality? ☐**yes** ☒**no**

(A supplementary confidentiality agreement must be filled in)

- If yes:

Can the thesis be online published when the period of confidentiality is expired? ☐**yes** ☒**no**

Date:

Preface and acknowledgement

Thanks to Professor Steinar Westlie Kristoffersen, our supervisor, and professor Halvard Artzen, our co-supervisor, for the attention they gave us, which was fundamental for the development of this master thesis. We would like to thank you for all the constant support, strength and excellent follow-up throughout the entire project.

We appreciate your help and support to keep us motivated. You saw our potential and managed to turn our weaknesses into positives, enabling us to deliver the best possible results.

A special sincere thanks to the study program coordinator, Arild Hoff, who gave us motivation and moral support. To all specialists who made themselves available to respond and had a huge participation in the result of this work. The members of Molde University College also deserve recognition for their commitment to excellent service.

We would also like to deeply thank all our family, friends and colleagues who supported us in one way or another, particularly during the development of this thesis.

As we write these acknowledgments, out heart overflows with emotion remembering all the moments we spent late night writing the final paper.

Thank you to Sharon for believing in my work and capabilities.
Thank you to Farhad, for always being there for me, keeping me calm, and motivating me to be a better person.

S&F Molde,
22.05.2023

Abstract

Equipping ships with an intelligent system can create a tremendous change in the marine transportation fleet. The importance of preserving the environment and not using fossil fuel can be one of its strengths. Also, due to human errors, which constitute the majority of maritime errors such as accidents, an intelligent system can help the crew and captain in detecting dangerous situations and increase the safety of the trip. These cases can be effective in the management and competitive performance of the sea fleet and cause passengers to choose the smart fleet for sea travel due to the quality of their travel. The present study examines maritime smart systems in short-distance voyages using neural network. For this purpose, three factors including passenger satisfaction, crew performance and environmental protection were selected and the variables affecting the mentioned factors were evaluated.
Optimization is another measure that was carried out in this research in order to increase the average importance of variables affecting the desired factors. By identifying low-impact variables, remove them from the system to increase the fleet's focus on other important variables and improve competitive and managerial performance. The three ports of Hamburg in Germany, Shanghai in China, and Molde in Norway were among the ports equipped with intelligent systems that were chosen to collect the data of this research. These two ports were chosen for the two reasons of using the energy storage system and the possibility of making short-distance trips. The purpose of this research is to evaluate the benefits of machine learning in prioritizing variables affecting triple factors, which can have a significant impact on achieving managerial and competitive performance in the intelligent maritime transport fleet in short-distance trips such as the trip between the city of Molde and the island of Hjertøya.

Keywords: D2D, Data Mining, Intelligent system, Vessel, Machine learning, Ship, Decision-making, Transportation, Logistics, Sustainability

Abbreviation

MUNIN	Maritime Unmanned Navigation through Information in Networks
AAWA	Automated Applications
D2D	Device-to-device
NWE	Northwest Experience
DC	Direct Current
IPS	Integrated Power System
VLC	Visible Light Communication
OFDMA	Orthogonal Frequency Division Multiple Access
GIS	Geographic Information System
RFID	Radio Frequency Identification
PSA	Port of Singapore Autorithy
VAHP-ANP	Voting Analytic Hierarchy Process-Analytic Network Process
IT	Information technology
RF	Radio Frequency
AI	Artificial Intelligence
ISP	Internet Service Provider
MLP	Multi-layer perceptron
RBF	Radial Basis Function
CATREG	Categorical Regression
GDP	Gross Domestic Product
ESS	Energy Storage System
PV	Photovoltaic
OPS	Onshore Power Supply
CI	Cold ironing
CRISP	Cross-Industry Standard Process
SPSS	Statistical Package for the Social Sciences
IBM SPSS	International Business Machines Statistical Package for the Social Sciences
ML	Machine Learning

Table of Contents

Preface and acknowledgement 5

Abstract 6

Abbreviation 7

List of Tables 11

List of Figures 12

Chapter 1 15

1.1. Introduction 15

1.1.2. Necessity of Research 19

1.1.3. Research Motivation 19

1.1.4. Research Objectives 20

Research Questions 21

1.2. Research Methodology 22

1.2.1. Indicators Affecting the Development of the Fleet 23

1.3. Research Assumptions 25

1.4. Data Collection and Analysis Method 26

1.5. Structure of the Thesis 26

Chapter 2 - A review of previous studies 28

2.1. Introduction 28

2.2. Research background 29

2.2.1. Intelligent network and device-to-device communication 30

2.2.2. Time based methods and sea transportation 32

2.2.3. Artificial intelligence algorithm and effective factors 34

2.2.4. The relationship between the research review and the present study 42

Chapter 3 44

Case Description 44

3.1. Introduction 44

3.2. A comprehensive framework for strategy formulation 45
3.3.1. Data mining process 46
3.3.2. Various functions of data mining 47
Classification 48
Evaluation and estimation 48
Forecast 49
Classification of similarity 49
Clustering process 49
Explanation and indexing 50
3.4. Regression 50
3.5. Different types of input data 50
3.6. Frequency distribution of data 51
3.7. Evaluation of the Data Collected from the Questionnaire 53
3.7.1 The age range of the respondents 53
3.7.2 Geographical Scope of Questionnaire Distribution 53
3.7.3 Effective variables based on Triple Factors 53
3.7.4. Stages of Evaluation of the Data Collected from the Questionnaire 55
3.8. Data classification in SPSS software 59
Chapter 4 64
Data and method 64
4.1. Introduction 64
4.2. Data and questionnaire 65
4.3. Proposed research method 67
4.3.1 Predictions for different groups 68
4.3.2 Evaluation of forecasts and triple factors 70
4.4. Findings Part I 74
4.4.1. Independent variable importance 76

4.5. Discussion.. 79

4.5.1 Evaluation of the correlation between the variables with the lowest priority 80

4.5.2. Evaluation of results based on optimization.. 87

4.6. Findings Part 2... 97

4.6.1. Independent variable importance.. 99

4.7. Discussion.. 102

4.7.1 Evaluation of the correlation between the variables with the lowest priority 103

4.7.2. Evaluation of results based on optimization... 109

Chapter 5.. 116

5.1. Conclusions 116

5.2. Answers on Research Questions' 118

5.3. Research summary.. 119

5.4 Managerial Implications 120

5.5. Limitations of the study... 121

5.6. Suggestions for further research 122

References.. 124

6. Appendix 128

List of Tables

Table 1 Questions based on the triple factors 52

Table 2 Information of different layers of the model 61

Table 3 Values Specific to Testing and training 62

Table 4 Error values for the proposed model 63

Table 5 Categorized and grouped questions based on three factors 64

Table 6 Predicted results for the experience criterion 67

Table 7 Predicted results for different groups 69

Table 8 Correlation between the main variables and passengers' satisfaction 82

Table 9 Correlation between the transformed variables and passengers' satisfaction 82

Table 10 Evaluation of triple factor and predictors 83

Table 11 Dependent variable: Satisfaction 84

Table 12 Evaluating the importance of predictor variables for the satisfaction factor........ 85

Table 13 Predicted results for different groups 87

Table 14 Predicted results for the experience criterion 88

Table 15 Comparison of the results according to the importance percentage of model variables 91

Table 16 Correlation between the main variables and passengers' satisfaction 105

Table 17 Correlation between the transformed variables and passengers' satisfaction ... 106

Table 18 Evaluation of triple factor and predictors 107

Table 19 Dependent variable: Satisfaction 108

Table 20 Evaluating the importance of predictor variables for the satisfaction factor 109

Table 21 Predicted results for different groups 111

Table 22 Predicted results for the experience criterion 112

Table 23 Comparison of the results according to the importance percentage of model variables 117

List of Figures

Figure 1 Scale of the worldwide autonomous ship market in 2019 and 2020, with a forecast for 2021 through 2030 13

Figure 2 Items that will be discussed in each chapter 25

Figure 3 VLC software and small-cell RF system (H. Zhang et al., 2018) 29

Figure 4 Algorithm of the integrated VAHP-AHP method (Alev Taskin Gumus et al., 2010) 30

Figure 5 Relationship of concepts in the proposed methodology (Kjetil Fagerholt et al., 2009) 32

Figure 6 "GIS" technology in the Rotterdam port control process (Esri, 2007) 34

Figure 7 Action map and its technology usage chart (Esri, 2006) 2

Figure 8 A view of the hybrid electric ship (Jae-Shik Park et al., 2001) 2

Figure 9 A view of the hybrid electric ship equipped with CI service (Ruoli Tang et al., 2018) 2

Figure 10 General requirements for equipping the system with CI technology (Edward A. Sciberras et al., 2015) 39

Figure 11 Non-linear standard model of data mining (Nick Hotz, 2023) 45

Figure 12 Frequency distribution of data completed by passengers 56

Figure 13 Frequency distribution of data completed by inspector 56

Figure 14 Frequency distribution of data completed by Captain 57

Figure 15 Frequency distribution of data completed by crew 57

Figure 16 The process of defining each of the target groups in the research 58

Figure 17 The process of defining the criteria of experience for each of the target groups 59

Figure 18 View of definition data for different variables 60

Figure 19 The most important variable affecting the pollution factor 70

Figure 20 Prediction accuracy in evaluating pollution factor 71

Figure 21 The most important variable affecting the passenger satisfaction factor 71

Figure 22 Prediction accuracy in evaluating satisfaction factor 72

Figure 23 The most important variable affecting the crew efficiency factor 72

Figure 24 Prediction accuracy in evaluating crew efficiency variables 73

Figure 25 Gain chart for different groups 74

Figure 26 Gain chart for the factor of previous experience of different groups in traveling by intelligent ship 75

Figure 27 Lift chart for different groups 76

Figure 28 Independent variable importance 77

Figure 29 Weighted residual of passenger satisfaction by the proposed model.................. 78
Figure 30 Weighted residual of crew performance by the proposed model........................ 78
Figure 31 Weighted residue of energy stability by the proposed model 78
Figure 32 Selected variables in order to perform optimization 79
Figure 33 Definition of independent and dependent variables of the model....................... 80
Figure 34 Selected variables (E10, E5 and S1) in order to optimize 81
Figure 35 Diagram of transformation process per variable S1.. 86
Figure 36 Diagram of transformation process per variable E5 86
Figure 37 Diagram of transformation process per variable E10 86
Figure 38 Profit graph for different groups after optimization.. 89
Figure 39 Profit diagram after the optimization process for the previous experience factor of different groups in traveling by smart ship.. 90
Figure 40 Lift diagram after the optimization process for different groups 91
Figure 41 Independent variable importance after the optimization process........................ 93
Figure 42 The most important variable affecting the pollution factor 94
Figure 43 Prediction accuracy in evaluating pollution factor.. 95
Figure 44 The most important variable affecting the passenger satisfaction factor 95
Figure 45 Prediction accuracy in evaluating satisfaction factor 96
Figure 46 The most important variable affecting the crew efficiency factor 96
Figure 47 Prediction accuracy in evaluating crew efficiency variables 97
Figure 48 Gain chart for different groups.. 98
Figure 49 Gain chart for the factor of previous experience of different groups in traveling by intelligent ship 99
Figure 50 Lift chart for different groups 100
Figure 51 Independent variable importance 101
Figure 52 Weighted residual of passenger satisfaction by the proposed model................ 102
Figure 53 Weighted residual of crew performance by the proposed model...................... 102
Figure 54 Weighted residue of energy stability by the proposed model 102
Figure 55 Selected variables in order to perform optimization 103
Figure 56 Definition of independent and dependent variables of the model..................... 104
Figure 57 Selected variables (E10, E5 and S1) in order to optimize 105
Figure 58 Diagram of transformation process per variable S1.. 109
Figure 59 Diagram of transformation process per variable E5 110
Figure 60 Diagram of transformation process per variable E10 110

Figure 61 Profit graph for different groups after optimization.. 113

Figure 62 Profit diagram after the optimization process for the previous experience factor of different groups in traveling by smart ship... 113

Figure 63 Lift diagram after the optimization process for different groups...................... 115

Figure 64 Independent variable importance after the optimization process...................... 117

Chapter 1

1.1. Introduction

In the last decade, there has been a significant increase in the topic of ships equipped with smart systems. An example of these studies is the MUNIN project (Jiri de Vos et al., 2021and MUNIN, 2016), which was about maritime unmanned marine navigation through a intelligent system. Also, the Advanced Autonomous Waterborne Applications partners project (Rolls-Royce, 2016) which was around the concept of AAWA is another example of this research.

The term "intelligent (smart) system" used in ships refers to the utilization of sensors, communications, the Internet of Things, such as Internet technology, automatic perception and acquisition of the ship itself, the marine environment, logistics, port and other information and data, and based on computer technology, automatic control technology and data processing and analysis technology. With such a system, ships can navigate, operate, maintain, and convey cargo intelligently (Yang, 2020).

The smart system in the ship is a technology that provides safe monitoring and management of the ship based on the structure of information technology. Sailing with ships equipped with smart systems has several advantages, such as economic efficiency in requiring less crew and simplifying ship design, in addition to making voyages safer (Jiri de Vos et al., 2021).

Another issue that makes the use of ships equipped with smart systems felt is the discussion of fleets' competition with each other and the need for marine fleets for ships equipped with intelligent systems in the ship market. As shown in Figure 1, provided by Next Move Strategy Consulting. the global autonomous ship market is projected to nearly double from 2019 to 2030. While the market size in 2019 was about US$6.57 billion (NOK 68.22 billion). It is expected to reach the scale of USD 10.74 billion (NOK 111.52 billion) by 2030 (Consulting, 2020).

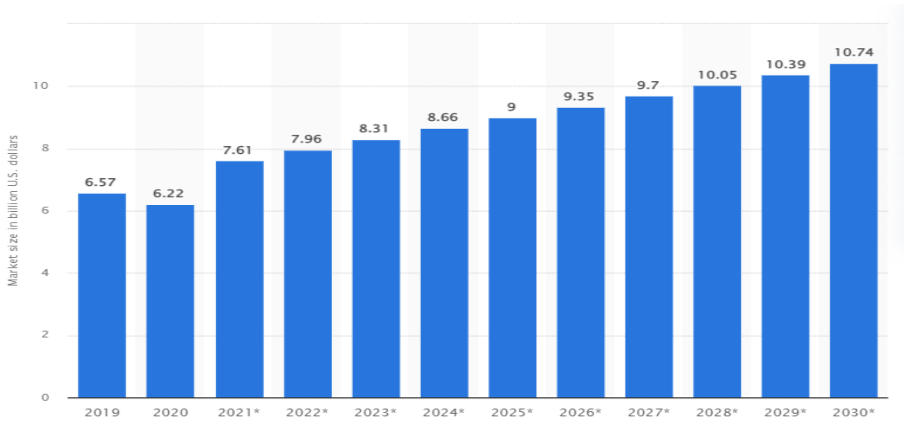


Figure 1 Scale of the worldwide autonomous ship market in 2019 and 2020, with a forecast for 2021 through 2030.[1]

The mentioned advantages of using the smart ship show that with smart system's control and monitoring, factors including passenger satisfaction, crew performance, and fuel stability can be improved. As a result of smart control and monitoring, travel safety can be increased (this factor affects the satisfaction of passengers). Also, the need for crew is reduced as a result of using the intelligent system on the ship, which naturally brings the crew's concern about unemployment. The smart system can be effective in simplifying ship design, which also implies energy sustainability (Jiri de Vos et al. 2021).

In the shipping fleet, which is a competitive system, the fleet must include issues such as energy sustainability (converting fossil fuel to electricity), risk prediction (fjord collisions), and crew excellent performance (DNV, 2018). This means that the shipping fleet may compete with rival fleets in order to improve its passenger satisfaction as well as increase passengers (such as a result of passenger satisfaction with crew performance).

Equipping the ship with an intelligent system can be one of the effective factors in increasing the satisfaction of passengers and the excellent performance of the crew and preserving the environment. Device-to-device (D2D) communication is a type of intelligent system that can be used as a technique to improve monitoring and control performance in intelligent transportation fleets. Especially in the sea transportation fleet with a large volume of passengers, this type of communication has the ability to improve management and competitive performance to a great extent.

[1] Autonomous Ships Market Analysis Report | 2021 - 2030 (nextmsc.com)

The reason for this is the direct and unmediated communication that leads to fast data transfer. By using device-to-device connection in the smart system, fluctuations are prevented and the efficiency of the system increases (Muzaidi Othman, et al. 2018) D2D communication is a technique for direct communication in an intelligent cellular network without the intervention of a base station. In this type of communication, the delay in sending information and the efficiency of the smart network is improved (Mohammad Haseeb Zafar et al. 2022). According to the things mentioned, using the D2D system in the smart system should be a suitable solution in terms of traffic and travel safety and smart control, which has an impact on three factors of passenger satisfaction, crew performance, and fuel stability.

1.1.1. State of Research Problem

Ports are one of the most essential and vital components in the country's capital and economy, and the growth and development of ports in the marine fleet will strengthen and improve the country's economic system (G.S Dwarakish, 2015). The increasing development of smart systems and the rapid expansion of marine fleet services have created a new era in the concept of control and monitoring. The decrease in travel safety can be caused by the lack of smart systems and sea traffic, considering the increase in the number of passengers (Frąckiewicz, 2023). Additionally, a ship equipped with a smart system can improve the performance of the crew, especially during hazardous situations. It is worth noting that concerns about potential unemployment resulting from the implementation of smart systems on ships can also impact the crew's performance (Jiri de Vos et al., 2021).

One of the important and distinctive features of the intelligent system is that it affects the management of monitoring and control conditions (Jun Yang et al., 2018). Utilizing a smart system on ships allows for comprehensive monitoring of the marine fleet, covering various aspects such as safety, environmental impact, trip duration, and crew concerns regarding unemployment. This systematic examination enables the establishment of favourable conditions to enhance three key factors: passenger satisfaction, crew performance, and fuel stability regulation.

According to the results (Jiri de Vos et al. 2021), crew performance and passenger satisfaction and environmental protection are the factors that get influenced by equipping the ship with a smart system. So far, researchers have not evaluated the variables affecting the mentioned factors. By prioritizing variables affecting each of the triple factors, the competitive and managerial performance of the marine fleet can be improved according to the existing conditions in maritime. Therefore, effective measures cannot be taken without prioritizing the variables affecting the triple factors in terms of improving management performance and competitive conditions in the marine fleet. By equipping the ship with an intelligent system, effective planning for ship's operation is provided, which makes it possible to inform about the danger and the appropriate access routes that, results in the improvement of shipping route effectiveness, to avoid wasting travel time (Sardis, 2023) and reduce pollution (Frąckiewicz, 2023). Hence, the primary objective of this research is to enhance the performance of managerial and supervisory roles by prioritizing the variables that have an impact on each of the aforementioned factors. By identifying and giving precedence to these influential variables, the aim is to optimize the effectiveness and efficiency of managerial and supervisory practices, ultimately leading to improved outcomes in relation to the factors under consideration.

Therefore, the current research identifies and strengthens the most important drivers of passenger satisfaction, crew performance, and environmental pollution.

In summary, the primary focus of this research is to address the issue of optimizing management and performance in the maritime industry by leveraging intelligent systems onboard ships. The key challenge revolves around comprehending and prioritizing the specific variables that influence crew performance, passenger satisfaction, and environmental conservation when employing these smart systems. This particular area of study has not been extensively investigated in existing researchers. The ultimate objective is to influence on improvement of safety measures, decreasing travel duration, and mitigating environmental pollution since they are existing problems in real-world industry (European Maritime Safety Agency, 2023).

1.1.2. Necessity of Research

In terms of the development and progress of the naval fleet, no country can be found that has not taken steps to rebuild and modernize its fleet in line with global standards. Life in coastal cities is different from other cities in terms of economic and environmental effects, and the quality of life in coastal cities depends on their ports (Øyvind Endresen et al., 2008).

In conclusion, it is necessary to create appropriate infrastructure for the development and expansion of the marine and passenger fleet in Norway due to its unique position in terms of access to open waters and proximity to neighbouring countries. Therefore, it is necessity for the research to examine the main factors involved in controlling and managing short-distance cruises with special attention. Identifying and prioritizing the variables affecting the three factors (passenger satisfaction and crew performance, and fuel stability) in the transportation sector of the marine fleet can provide more accurate estimates than the evaluation of the effects of the smart system. This research can provide conditions by prioritizing and optimizing the effective variables to improve the management and competitive conditions of the marine fleet by focusing on the variables with higher priority from the point of view of different groups, including passengers, crew, captain, and inspector.

1.1.3. Research Motivation

This research is specifically based on the "Smart Molde" project owned by the Municipality of Molde, which focuses on creating a non-fossil sea transport alternative and is interested in improving access to Hjertøya outside Molde by the Northwest Experience (NWE) and making its use more widespread for the general public. Publicizing its use has encouraged the researchers to conduct this research. Considering this goal, a technical conceptual study was conducted focusing on factors including passenger satisfaction, crew performance and energy sustainability for the deployment of the smart system on the ship. The influencing variables, which are safety, traffic, crew unemployment, travel time, environmental impact, and economic cost, were included in the form of a questionnaire and were completed by different groups of passengers, crew, and captain. The mentioned challenges that have an impact on the control and management of the fleet are the main motivations of this research that play a role in the development of the smart marine transportation fleet. One of the key challenges in the implementation of electronic systems embedded in the smart system is to ensure their compatibility with other systems and components.

These systems must be designed to work with other technologies, such as communication systems and control algorithms, to ensure that the intelligent system can operate safely and efficiently. In addition, after determining the most effective variables, it was tried to optimize the intelligent system to increase the average importance of all variables. By optimizing the variables, the marine fleet can be more successful in the competitive discussion with other fleets by relying on the variables with higher priority. Ultimately, our research contributes to a more sustainable and efficient future for coastal communities in Norway and beyond. This research could pave the way for Northwest Experiences (NWE) to use the smart marine fleet along the Norwegian coast in a way that increases passenger satisfaction and crew performance. Also, by equipping the marine fleet with a smart system, an effective step should be taken in the issue of environmental pollution and not using fossil fuels.

1.1.4. Research Objectives

One of the most critical challenges of maritime transport is the prioritization of the main variables in order to invest in energy efficiency. As a result of the priority of the variables, it is determined which priority should be given more importance in order to be more successful in the competitive debate (Ángeles Longarela-Ares et al., 2020). This research aims to evaluate the use of the smart system in the ship to evaluate the crew efficiency, provision of services with appropriate quality for passengers, and energy sustainability. These objectives could provide several ideas in the field of management in order to create the efficiency and expandability of the intelligent system.

Considering the growth of the population, it is expected that the number of trips with different fleets will increase, of which the marine fleet is one of these subsets. Although with the development of wireless systems, conditions have improved to prevent passengers from wasting time, but none of these technologies can compare with the benefits of using a smart and data-based system in the marine fleet (Wartsila, 2022).This type of solution can improve environmental protection, reduce travel time and increase travel safety (Latia et al., 2010 and Jiri de Vos al. 2021).

This research tries to achieve providing suitable conditions in the managerial and competitive aspects of the marine fleet by prioritizing the variables affecting passenger satisfaction and crew energy and performance. Due to the importance of competitive and regulatory concepts, it is difficult to provide services with good quality (SINAY, 2022).

Therefore, a method should be proposed to improve the service quality parameters compared to the previous techniques in the marine fleet and provide more suitable quality services. Due to the increasing importance of intelligent systems, in this research, a conceptual model based on the completion of questionnaires by different groups, which are passengers, crew, captain, and inspector, has been presented in this research to improve the efficiency of the marine fleet.

Research Questions

This research seeks to answer the following questions to determine which variables have the greatest impact on the three factors, and by focusing on them, the research goals can be achieved faster, more accurately, and cheaper. The questions are:

Q1: Which variables are more accurate in predicting the competitive and managerial performance of the shipping fleet based on the proposed intelligent system?

Q2: Does a neural network based on a machine learning algorithm work properly in a smart maritime transport system?

Q3: What is the prioritization of variables in order to improve competitive performance and intelligent system management?

Q4: Which of the low-priority variables can be improved through the quality value optimization process?

These questions have been raised to check the correctness of the neural network in determining the variables affecting the triple factors and the focus of the marine fleet on the variables with higher priority to achieving successful competitive and managerial performance.

In order to clarify what neural networks are, in a loose sense, neural network models are cognitive task algorithms for learning and optimization based on ideas from research into the workings of the brain (Berndt Müller et al., 1995).

The conceptual model in the current research includes three interconnected and integrated factors that examine the problem in question together. In this research, using a neural network, various variables that affect the control and management of the marine fleet have been investigated. By collecting information through a questionnaire and defining a conceptual model based on a neural network, variables affecting passenger satisfaction, fuel stability and crew performance were prioritized and analyzed.

The main goal is to provide suitable conditions in the managerial and competitive dimension of the marine fleet by prioritizing variables affecting passenger satisfaction, pollution and crew performance. To achieve this goal, a questionnaire was prepared and completed by different groups of volunteers including passengers, crew, captain and inspector, and at the very last an optimization measurement.

1.2. Research Methodology

In the current research, a questionnaire was designed based on variables affecting the triple factors, which are passenger satisfaction, ship crew performance, and energy sustainability, and was completed by people including four groups of passengers, crew, inspector, and captain. The three ports of Hamburg in Germany, Shanghai in China, and Molde in Norway were among the ports where some ships are equipped with intelligent systems that were chosen to collect the data for this research. The age range of the people who answered the questions was between 35 and 55 years for the inspector and captain groups. The age range for the ship crew group was between 30 and 45 years, and for the passenger group, the age range was between 25 and 60 years. More information regarding how the candidates were approached will be explained in the chapter related to the data collection. The questionnaire was prepared based on the study of research literature, and a list of factors affecting the competitive performance and management of the marine fleet was listed. Afterward, the effectiveness of each of the three factors, which are passenger satisfaction, crew performance, and fuel stability, was investigated. After collecting the questionnaires, the factors were analyzed and prioritized using the hierarchical analysis method.

The vivid steps of what has been done in this section are described below:

1) **First step:**

A detailed search was carried out utilizing library techniques to assemble the study material and lay the theoretical groundwork. Investigating pertinent and citable papers from respectable academic journals and publications were required for this. The criterion used to select a number of journals was their scientific level and impact factor. To gain further knowledge and insights, trustworthy websites and internet resources dedicated to the study's topic were explored. Traditional and digital sources were used in the search process to guarantee a complete and current collection of pertinent literature and theoretical frameworks.

2) **Second step:**

In the second stage, a questionnaire was prepared based on the findings of the first stage, which was given to two engineering science researchers who had expertise in computer and civil engineering to test and review the questionnaire. The purpose of this test was to evaluate the scientific level and comprehensibility of the questions for ordinary people (the questionnaire was sent to questioners via the Internet).

Initially, the questionnaire was prepared separately for each of the different groups. After the evaluation of the researchers, their opinion was that all the questions should be completed by different groups in order to achieve a comprehensive evaluation of the subject. For example, passengers do not have information about the energy consumption of the smart system, but their opinion can be effective in their evaluation of the amount of energy consumption through the cost of purchasing a ticket for a trip with a smart ship. After applying the proposed amendments, another questionnaire was prepared based on the influencing factors with a new format and was distributed among the respondents (including passengers, ship crew, captain, and inspector) and finally, the questionnaires were collected and analyzed.

3) **Third level:**

In this part, by analyzing the results, the desired factors and variables were evaluated and prioritized to identify the main variables. Variables that had a high priority were selected and an attempt was made to improve the qualitative value of the desired variables by identifying low-impact factors and performing the optimization process.

1.2.1. Indicators Affecting the Development of the Fleet

In order to achieve the goals of this research, the factors related to the development of smart maritime transport should be investigated as much as possible. The development of smart transportation in the maritime industry can be examined from multiple perspectives, such as competition, services, and supervision. Each of these dimensions encompasses specific factors that contribute to the advancement of maritime transportation (Jiri de Vos et al., 2021). In this section and its subcategories, examples of research conducted in the field of maritime transportation and related factors are evaluated.

- Investor attraction strategy

(J. David Hunger et al., 2001) defines strategic management as a set of management decisions and actions that determine the long-term performance of an organization. Strategic management includes strategy formulation, strategy implementation and strategy control (J. David Hunger et el., 2001). Equipping the marine fleet with a smart system is expensive. On the other hand, the cost of maintenance and repairs of this smart system can affect the economic conditions of the fleet. From the concept of (Hunger et al., 2011), it is inferred that the government can act as an investor by paying subsidies or other incentives and facilities, which is an important step in the desire of other fleets to use the smart system.

- Educational strategies

Research shows that the performance of organizations that deal with strategic planning is more and better than other organizations. Achieving a proper communication link between an organization's environment and its strategies, structure and processes has positive effects on its performance (J. David Hunger et el., 2001). It is inferred from this concept that by prioritizing the variables affecting competitive and managerial performance, it is possible to define a type of operational plan that, under training strategies, will improve passenger satisfaction and crew performance and preserve the environment.

- Advanced and smart control systems

The use of technology has a significant impact on parameters such as capacity, speed, reliability and trust in the shipping industry. Also, these technologies have a great impact in creating balance in different elements of transportation (Jiri de Vos et al. 2021).

- Safety

The source of many risks in shipping is the human factor. Human factors such as fatigue, human resource supply and employment issues, organizational management problems, and ship design and construction challenges are among the most important current and future safety challenges in maritime transportation (Risto Jalonen et al., 2009).

- Environmental Protection

Due to the pollution caused by the use of fossil fuels and the damage it has on the environment. The issue of clean fuel is of particular importance. It is possible to use the smart grid for optimal and effective use of solar and wind energy (Jiri de Vos et al. 2021).

Therefore, by equipping the ship with an intelligent system, clean energy can be used to provide propulsion energy, which has a significant contribution in preserving the environment and reducing pollution.

1.3. Research Assumptions

This scientific research is based on a series of assumptions that by determining these assumptions, the desired goals can be achieved. These assumptions have been inferred based on the study of the sources mentioned in the introduction section of the present study.

To conduct the present research, the following assumptions have been considered:

1. The establishment of smart shipping lines has an effect on improving travel safety. Things such as wear and tear of the marine fleet, the presence of dangerous fjords, and human error can endanger the health of passengers, and equipping the ship with a smart system will greatly help the crew in times of danger.

2. There is the possibility of improvement in variables such as pollution, length of travel time, economic cost, and concern about crew unemployment in ports equipped with smart systems, which should be prioritized based on the opinion of marine fleet experts. For example, in seaports such as China, due to the large number of passengers and sea voyages, the issues of economic cost and length of travel and the concern of crew unemployment become very important. The port of Hamburg, Germany, has been awarded the title of "Green Capital of Europe" for the promotion of environmental standards and the use of renewable energy.

   Therefore, the issues of pollution and concern about the unemployment of the crew and the safety of the trip are very relevant compared to other variables in this port.

3. The energy consumption of the ship and the duration of the trip are different according to the category of ships and seaports. According to the studies conducted in the current research and presented in chapter 2, smart ships can use two systems of energy supply from land and energy storage system. Also, a number of seaports are equipped with a smart monitoring system that affects the duration of the trip. Therefore, in this research, smart ships equipped with energy storage systems and seaports equipped with monitoring systems have been used.

4. According to marine fleet experts, smart ships (in terms of energy supply) are not able to travel on some routes. According to the way of energy supply, smart ships should travel on routes where the sea ports of origin and destination are equipped with the necessary system for their energy supply. For example, a smart ship equipped with an energy supply system cannot travel on a route where energy storage systems are used in its ports.

1.4. Data Collection and Analysis Method

In this research, the required information was obtained through library studies, questionnaires, and scientific articles. Then, according to the problem, a suitable conceptual model was defined to increase crew performance, passenger satisfaction, and energy sustainability. Various variables such as travel safety, travel duration, and costs related to the ship itself (fuel consumption) and the ship crew's concern about unemployment were considered in the definition of the conceptual model. In the next step, the second objective function was created to increase the quality of the desired variables based on the optimization process.

The way to achieve the mentioned goals is to choose ships that are equipped with intelligent systems so that different groups of people, including crew, passengers, captains, and inspectors, complete the questionnaire. For this purpose, a questionnaire was designed and distributed in the ports of Hamburg in Germany, Shanghai in China, and Molde in Norway. After collecting information in this research, processing and analysis of the obtained raw data were used according to the needs of descriptive and inferential statistics methods.

Next, evaluation and conclusions were made from the analyzed data. SPSS (Statistical Package for Social Sciences) modeler software was used for data analysis.

1.5. Structure of the Thesis

This research comprises five chapters that aim to provide a comprehensive analysis of the subject matter. The structure of the thesis is as follows:

- **Chapter 1:** The framework of the thesis is generally explained, which includes the purpose of the research and its necessity, as well as a clear statement of the researched problem and its solution method. Also, explanations are provided regarding the method of collecting thesis information and the users of its results, and the temporal, spatial, and thematic scope.

- **Chapter 2:** It examines the background of the research, and in this regard, the related researches conducted have been examined. Also, the literature on the subject and the introduction of the study case have been discussed.
- **Chapter 3:** The conceptual model of the research is explained and the method of the hierarchical analysis process is fully described. Also, the method of data collection and the statistical population have been discussed.
- **Chapter 4:** Data analysis and research findings are discussed. In this chapter, according to the information collected by the questionnaire, the information obtained from it has been analyzed and the most important factors of maritime transport management and control have been identified and ranked. After prioritizing the variables in order to improve the quality of the proposed network, the optimization process was performed on a number of variables that were ranked low.
- **Chapter 5:** The final chapter of the thesis encompasses the discussion, conclusion, and recommendations. It provides appropriate suggestions have been provided regarding the adoption of correct operational policies regarding the optimal management of this industry in the country. A summarized view for the main items discussed in each chapter is presented in Figure 2.

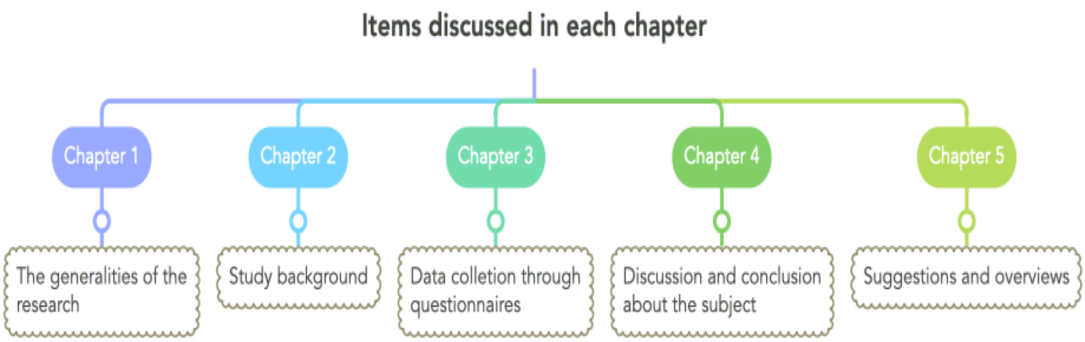


Figure 2 Items that will be discussed in each chapter.

Chapter 2 - A review of previous studies

2.1. Introduction

According to (Marisa Smith et al., 2017), management performance is a highly contentious principle and concept, characterized by the existence of numerous, and at times inefficient, approaches to attaining it. In the absence of any correct and operational definition of managerial performance within the system, diverse interpretations and inferences are likely to arise among managers and individuals employed in the system, influenced by their own perceptions. As a result, the generally accepted definition (continuous control of employees working in the system and monitoring of their performance) of this concept faces various problems and dilemmas. Hence, the expert definition and inference in this concept assume a fundamental role in achieving optimal performance and efficiency within the system.

According to (Michele Acciaro et al., 2014), seaports have always experienced a high energy demand due to their close proximity to residential and urban areas, as well as their crucial role in the transportation industry. In recent years, there has been a growing recognition of the need to control and manage all port activities to focus on energy management and efficiency, with the aim of preserving the environment. The adoption of advanced technologies like shore power supply and renewable energy in shipping ports requires further investigation and attention to achieve substantial advancements in active energy planning and management.

Although only a few port experts have taken action to implement energy management policies thus far, it is crucial for officials to proactively engage in conscious energy management as part of planning and developing economic activities in seaports. Through effective energy management, ports can enhance their competitive performance, as noted by (Michele Acciaro et al., 2014).

Consequently, it can be concluded that the primary goal of implementing a marine smart network, with a focus on preserving the environment and ensuring travel safety, is to provide necessary solutions to prevent environmental pollution and mitigate potential risks, particularly when navigating through fjords, through appropriate actions and measures (Michele Acciaro et al., 2014).

2.2. Research background

In contemporary times, transportation issues and challenges have escalated, encompassing concerns such as environmental pollution, depletion of energy resources, heightened accident damages, supervision and management difficulties, time wastage, and mounting transportation demands. To address these pressing problems, the intelligent transportation system incorporates a range of techniques and expertise, including safety concepts, environmental protection measures, and advanced communication technologies. The application of these tools aims to enhance the management standards and overall quality within the marine fleet (Jiri de Vos et al., 2021).

In the context of a smart ship, effective energy and fuel management play a fundamental role in enhancing ship efficiency and minimizing energy supply costs (C. Patsios et al., 2012). By employing appropriate energy management methods, smart ships offer several advantages over traditional and common ships. These advantages include more efficient energy utilization, optimized distribution and control of energy, increased reliability, optimal space utilization, and increased overall efficiency (C. Patsios et al., 2012).

(Tashakori Abkenar et al., 2017), In their study, employed a genetic algorithm to evaluate and manage fuel cell power in fully electric and smart ships. Electric ships are recognized as an effective solution for reducing greenhouse gas emissions and protecting the environment.

The utilization of clean energy sources like fuel cells further aids in minimizing environmental pollution. Due to the relatively low voltage level of fuel cells, they are arranged in series to increase the overall voltage level. However, this voltage level is not suitable for ship loading and unloading operations. To address this, a direct current (DC)-to-direct current converter is employed to adjust the voltage level and raise it to the necessary range. It is important to note that incorporating the DC-to-DC converter into the intelligent system results in increased economic costs. To achieve a balance between increasing the voltage level of fuel cells and managing the associated economic costs, the study utilizes a form of artificial intelligence called genetic programming. This approach utilizes mathematical equations to effectively establish correlations between the required input variables and the desired characteristics. By employing the genetic algorithm, it becomes possible to develop an equation that relates independent input variables to the target variable, which in this case is the fuel cell output voltage (Tashakori Abkenar et al., 2017).

The method presented in this research, proposes that the suitable input parameter, determined by the genetic algorithm, serve as a criterion for achieving the desired output voltage.

According to (Norbert Doerry et al., 1996), integrated power systems (IPS) play a crucial role in supplying electrical power to various types of ships, including surface combatants, aircraft carriers, amphibious ships, auxiliary ships, sealift vessels, and high-value commercial ships. The IPS serves ship service loads as well as electric propulsion needs. In the context of IPS, including the smart system of marine vessels, sudden fluctuations in system variables can have a significant impact on optimal and effective performance. Hence, it becomes essential to evaluate all uncertain parameters of the intelligent system, such as loads with uncertainty. The electrical energy supply system in intelligent ships must fulfill the requirements of the propulsion system while simultaneously catering to the needs of passengers. In the ship's energy supply system, the occurrence of abrupt variable fluctuations within the smart system, coupled with pulsed energy demands during peak travel hours, can increasingly influence the quality and performance of the intelligent network. To enhance performance and achieve higher quality standards, it becomes imperative to mitigate the effects of load fluctuations within the intelligent system (Muzaidi Othman et al., 2018).

2.2.1. Intelligent network and device-to-device communication

Another type of smart network that is widely used today is device-to-device communication. Many problems that occur in wireless communication lines can be prevented with the advancement of technology. Challenges such as lack of communication and delayed notification which can arise due to fluctuations among other causes, can now be effectively prevented through the application of device-to-device communication techniques. This section highlights the research conducted in the field of device-to-device communication, emphasizing the inclusion of decision-making factors and quick responsiveness to existing needs and energy management considerations (Mohammad Haseeb Zafar et al., 2022)

(Muhammad Usman et al., 2015) presented an architecture based on a device-to-device hierarchical model in which a controller acts to reduce the number of communication links to connect to the cloud. According to the results, this D2D hierarchical communication architecture has an effective effect in reducing energy consumption.

The use of the central control system in this model allows the system to be efficient without causing damage to the infrastructure and creating the optimal condition of the centres (Othman et al., 2015). In this system, several smart ships can be connected to the central control system without reducing the optimal performance of the smart system.

The Visible Light Communication (VLC) technique has been put forth as a promising system, especially in cases where radio frequency communication resources are limited, making it a suitable alternative. This system aims to enhance efficiency and performance in internal communications within various environments. By utilizing VLC and networks comprising small cells, the overall system performance within internal networks experiences significant improvement. (H. Zhang et al., 2018) proposed a cellular network that combines visible light and radio frequency communication, leveraging the concept of Orthogonal Frequency Division Multiple Access (OFDMA) for effective implementation.

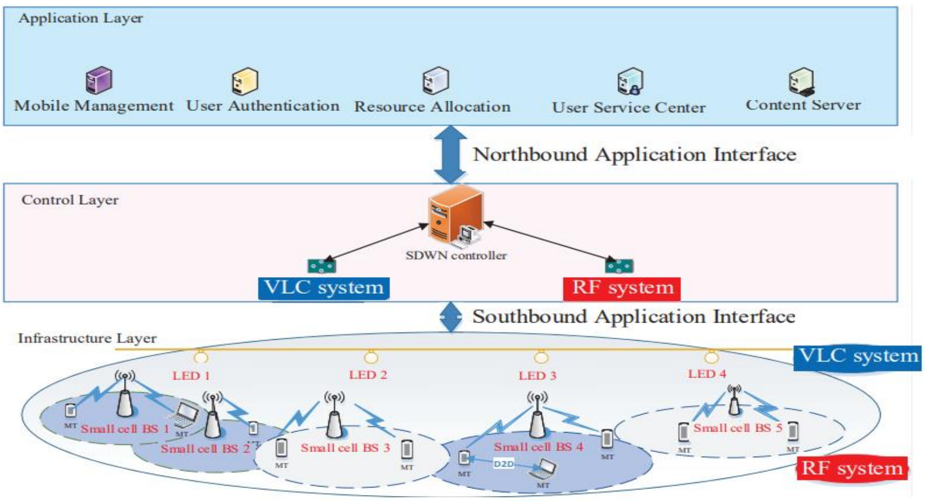


Figure 3 VLC software and small-cell RF system (H. Zhang et al., 2018)

Significant attention was devoted to examining key and critical issues concerning energy in visible light and radio communication cellular networks. Researchers formulated a model that encompassed energy management and efficiency, with optimization being a key consideration (H. Zhang et al., 2018). This architectural approach presents a suitable solution, particularly in scenarios where the efficiency of the smart system needs to be enhanced, and multiple smart ships must connect to a limited resource due to communication resource constraints. By adopting this system, chosen to address the scarcity of communication resources, variables related to travel safety and environmental preservation remain unaffected by negative impacts.

2.2.2. Time based methods and sea transportation

(Alev Taskin Gumus et al., 2010) evaluated a research design based on selecting the type of marine vessel through an integrated VAHP-ANP method for high-speed public transportation in the Bosphorus Strait. These researchers generally categorized transportation planning phases into three groups of variable factors, time variables, financial costs and decision-making levels. According to the statistical data, they investigated the role of suitable vessel on the quality and speed of travel in short trips and emphasized that choosing the most suitable vessel according to the sea and travel distance can play a significant role in providing services.

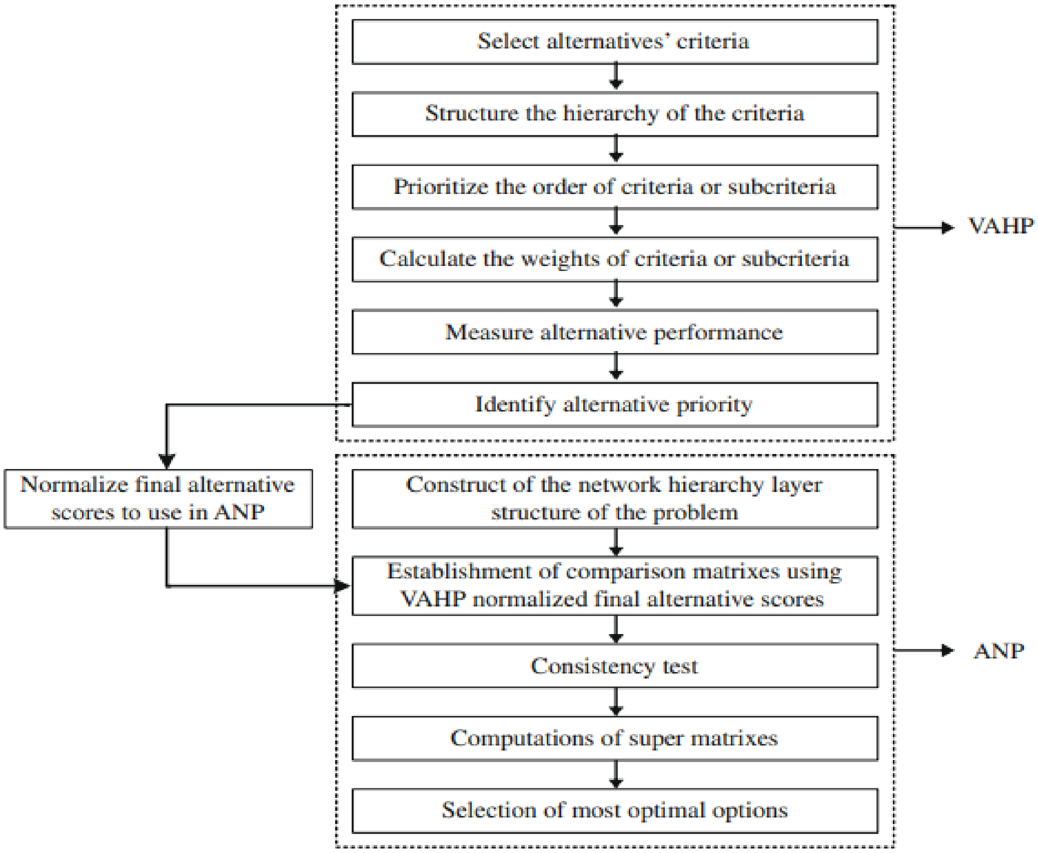


Figure 4 Algorithm of the integrated VAHP-AHP method (Alev Taskin Gumus et al., 2010)

In their research (Alev Taskin Gumus et al., 2010), it was determined that the type of ship has a significant impact in determining the quality and speed of the trip. However, the researchers did not prioritize the factors involved in ship selection. Consequently, in the present research, the type of ship, specifically distinguishing between a ship powered by fossil fuel and a smart ship, was considered as variables that influences the triple factors.

According to (Veerachai Gosasang et al., 2011), a study was conducted on the port of Bangkok, which holds significant importance as a major trading port. The researchers employed different methods to assess the exchange power, focusing on evaluating the main variables. Specifically, they explored two techniques: time series analysis and regression analysis, with the aim of prioritizing the key variables of interest.

The study investigated several variables, including export volume, gross domestic product import, exchange rate, inflation rate, and interest rate. These variables were examined to determine their influence on the port's capacity, providing an understanding of its ability to handle goods and products.

The researchers utilized neural networks as a means to predict the port's capacity. By employing this method, they identified the factors that impact the port's capacity and introduced them as input to the neural networks for prediction.

Based on the findings of the study, it was concluded that the squared error method was more powerful for prediction. The results of the modelling process demonstrated the efficacy of this approach (Veerachai Gosasang et al., 2011).

(Kjetil Fagerholt et al., 2009) present an advanced method for managerial decision-making in commercial transportation. They assert that their planning framework revolves around time optimization. During their research in Norwegian shipping, the researchers discovered several management problems. These problems encompassed structural issues within the marine fleet and ambiguous conditions of contract analysis. These challenges underscored the necessity for strategic and flexible planning support in the industry.

According to (Risto Jalonen et al., 2009), safety is recognized as a critical concern within the marine fleet. Senior managers and experts involved in the industry require pertinent information during the decision-making process to effectively control and manage safety. The availability of adequate information is essential for identifying potential issues, devising appropriate action plans, issuing relevant directives, and implementing them accordingly.

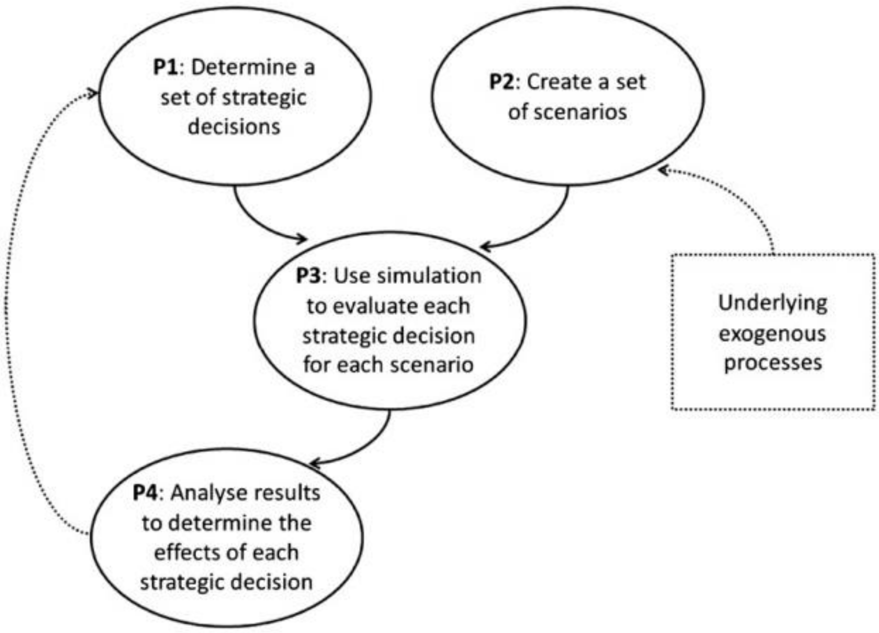


Figure 5 Relationship of concepts in the proposed methodology (Kjetil Fagerholt et al., 2009)

As a result, for comprehensive planning in the field of maritime safety, complete and comprehensive information is needed in all relevant fields. In the maritime industry, safety is of key importance, and the factors affecting safety in this industry alone have the ability to cause an irreparable accident. By considering input variables, the issue of travel safety can be evaluated from different aspects. These factors, along with the complexity of safety, have caused risk reduction to be a difficult and dangerous process. Safety in the maritime fleet is to protect the life and property of all the passengers and crew of the ship. Safety in the field of marine fleet is a specialized matter, and passengers are not familiar with the necessary measures in case of danger (Risto Jalonen et al., 2009).

2.2.3. Artificial intelligence algorithm and effective factors

In this section, we focus on research that utilizes machine learning techniques to analyze the factors influencing the management of smart networks in the marine fleet. By examining various aspects, including energy and environmental preservation, as well as travel safety, researchers have employed different algorithms that can provide valuable insights for the current study.

Previously, we explored research and studies pertaining to the factors and beneficiaries that play a significant role in this domain. In this section, we delve into studies that utilize artificial intelligence algorithms to assess energy sustainability, passenger satisfaction (in terms of travel time), and crew performance (including quick response to emerging needs and ensuring travel safety).

In the realm of intelligent transportation, the utilization of advanced Geographic Information System (GIS) technology enables the integration of information from various sources into a comprehensive picture. This integrated approach facilitates the control and management of marine fleets. The implementation of an intelligent system empowers improvements in performance, efficiency, and environmental management within the marine fleet and shipping lines. It also enhances safety measures and enables swift responses to emerging needs. Notably, all the images are captured using GIS technology, which enables the monitoring of routes during sea voyages (Esri, 2007).

Consequently, the following two key points can be deduced from the aforementioned information:

1. With the aid of GIS technology, it becomes possible to select the most suitable route for sea voyages by considering factors such as safety, fuel stability, and trip duration.
2. GIS technology enables the enhancement of management and service performance in the marine fleet by evaluating and managing ship movement time and general information, including ship movement routes and fjords.

Figure 6 "GIS" technology in the Rotterdam port control process (Esri, 2007)

In England, the waterways of this country are controlled by this technology, granting marine fleet managers and experts' significant authority in managing and controlling critical situations. For instance, in Rotterdam port, the implementation of this technology along with the utilization of satellite images has greatly enhanced port monitoring and management capabilities (Esri, 2007).

One of the effective and important functions of this advanced technology is to improve the safety of the marine fleet. With the help of this technology, the ability to use port images for communication between different parts of the system is provided. By using this advanced technology, it becomes possible to evaluate and integrate images received from several different sources including, satellite and aerial imagery. These images are then displayed on the screen and transmitted to a secure information network for the purpose to review all results and comprehensive analysis. By employing the "GIS" technology and the proposed intelligent system, the arrival and departure times of ships, as well as the traffic of ships within the marine fleet, can be controlled using smart cameras (Esri, 2006).

Figure 7 Action map and its technology usage chart (Esri, 2006)

In 1993, an intelligent automation system based on the new "RFID" technology was launched in the port of Singapore to manage the financial cycle of the cargo terminal. The utilization of "RFID" tags creates a smart network that enables multi-dimensional tracking in conjunction with transmitters strategically located throughout the designated area. Notably, in this port, the management of the arrival and departure of ships, as well as the initial tracking of cargo, are carried out jointly and simultaneously through the combined employment of "RFID" and "GPS" technologies (Jeetendre Narsoo et al., 2009).

The inception of this technology traces back to 1993, when the port of Singapore collaborated with the Port of Singapore Port Authority (PSA) Texas Company on a development project that incurred a significant cost of 900 million dollars. Through the implementation of centralized control and management of facilities, the port of Singapore has emerged as one of the world's largest ports. The utilization of this advanced system enables passengers and experts to intelligently track their destinations, signifying a notable achievement in enhancing efficiency and effectiveness (Jeetendre Narsoo et al., 2009).

The implementation of radio frequency identification (RFID) technology has greatly contributed to the effective and auxiliary communication among international ships in the port, as well to the control of security and surveillance systems by means of Internet Service Provider (ISP) network engineering. Notably, the utilization of this advanced technology has been mandated by the International Maritime Organization for all major commercial ports. Furthermore, the integration of indoor positioning systems "IPS" in providing services based on location, along with the facilities of smart mobile phones and the advanced generation of the radio frequency identification (RFID) system, take an effective step in tracking the intended targets (Jeetendre Narsoo et al., 2009).

According to the results of (Esri, 2007), (Esri, 2006), and (Jeetendre Narsoo et al., 2009), travel time is one of the main factors in passenger satisfaction. Consequently, in the present study, an evaluation of trip duration was conducted by administering questionnaires exclusively at ports that were equipped with the system of registering the arrival and departure of ships.

(Oludolapo Olanrewaju et al., 2012) showed that the implementation of a long-term economic development plan for a country requires establishing a correct relationship between the energy component and the economy. Meanwhile, in order to choose a model for predicting energy consumption, one should seek to establish a logical method between the variables. In this particular investigation, methods based on artificial intelligence algorithms based on multi-layer perceptron neural networks (MLP) and radial basis function (RBF) were employed to calculate energy consumption in the South African industry between 1933 and 2000.

The study utilized gross domestic product (GDP) as the input variable and energy consumption of the industrial sector as output. Additionally, the year 1995 was designated as the base year for GDP, and the results obtained using neural networks showed that the predicted values had a lower absolute error percentage compared to other models. According to the correlation coefficient, the results showed better performance of RBF networks over MLP networks (Oludolapo Olanrewaju et al., 2012).

The growing expansion of advanced technologies and renewable energy sources in various systems has paved the way for the integration of clean energy into power and energy production systems.

By using the potential of renewable energy sources in conjunction with marine energy systems, ships can be better equipped to deal with critical conditions encountered during sea voyages. Moreover, the utilization of renewable energy sources, such as solar or wind energy systems, onboard ships offer a promising solution to mitigate the environmental pollution caused by fossil fuel-based propulsion systems (Fotis D. Kanellos et al., 2016 and Muzaidi Othman et al., 2018).

(Latia et al., 2010) evaluated and investigated the time spent traveling distance on cruises using data mining tools and techniques. They were able to reduce travel time and predict patterns according to passenger journeys. Specifically, the researchers estimated the travel time for each passenger by leveraging data from the London database. By identifying the stations most frequently utilized by passengers and proposing an efficient model, they suggested a route that would reduce the time spent per trip.

The integration of renewable resources in the technology of energy production systems, due to their unstable nature, has faced a fundamental challenge for independent transportation systems. To address this challenge, the utilization of energy storage system technique (ESS) has been proposed as a solution to enhance the performance and efficiency of renewable-based systems (Muzaidi Othman et al., 2018). Due to the uncertainty in the amount of energy needed due to different conditions and variable services of the ship during different trips, the simultaneous use of energy storage system and energy systems can have significant effects on improving the performance of the ship and reducing fuel consumption. The diesel generator and photovoltaic “PV” production power are used to supply the ship's energy, and the surplus of the produced energy is stored in the energy storage system, and the power stored in the ESS can help meet the demand for the ship's energy system during peak hours. This ESS integration effectively addresses the ships dynamic energy requirements (Jae-Shik Park et al., 2001 and Chang, 2012 and Muzaidi Othman et al., 2018).

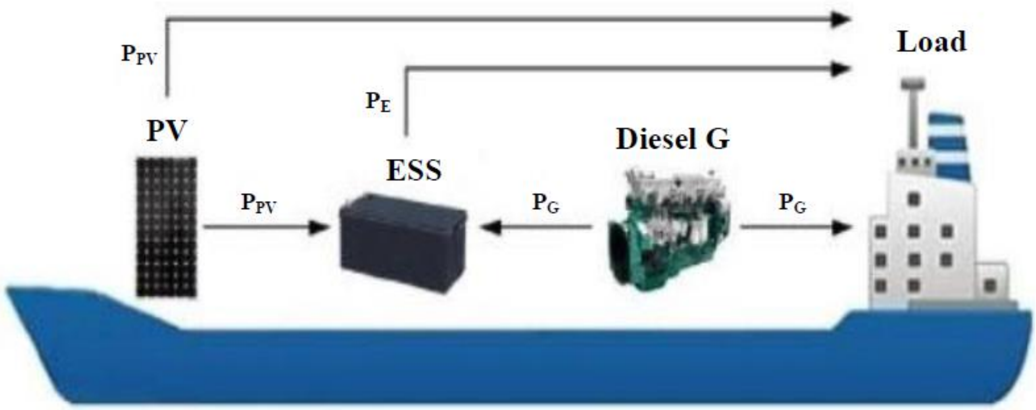


Figure 8 A view of the hybrid electric ship (Jae-Shik Park et al., 2001)

According to the International Maritime Organization (IMO), the shipping industry's involvement in international maritime trade has led to a substantial 500% rise in environmental pollutants and greenhouse gas emissions in recent decades. As a result, the contribution of international transportation to climate change is undeniable, with approximately 1.8% to 3.5% of global greenhouse gas emissions being attributed to this industry. To address this pressing issue and protect the environment, it is crucial to prioritize the adoption of suitable policies within the marine shipping industry while also focusing on the design of engines and ship hulls (Chang, 2012). These efforts are essential in controlling greenhouse gas emissions and ensuring environmental preservation in the shipping sector.

This system is designed in such a way that the energy demand of the ship in the port is supplied from the shore power grid instead of the diesel generator. In this system, the operation of the ship's generators has reached the minimum possible, and there is no need to continue the operation of the diesel generators, and they are cooled. This causes the pollutants to be significantly reduced during the anchoring of the ship in the port. By using OPS, when the ship is stopped in the port, the energy charging continues to provide services with the help of the shore network, which is called cold ironing (CI) (Chang, 2012 and Ruoli Tang et al., 2018).

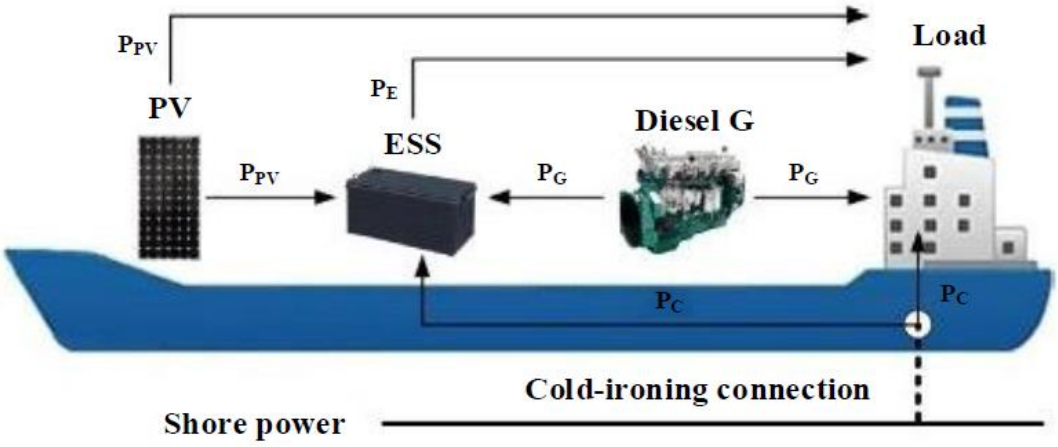


Figure 9 A view of the hybrid electric ship equipped with CI service (Ruoli Tang et al., 2018)

The basic and infrastructure requirements are shown in the figure below in accordance with the IEC/ISO/IEEE 80005-1 standard for creating a CI service in the smart network of the marine fleet.

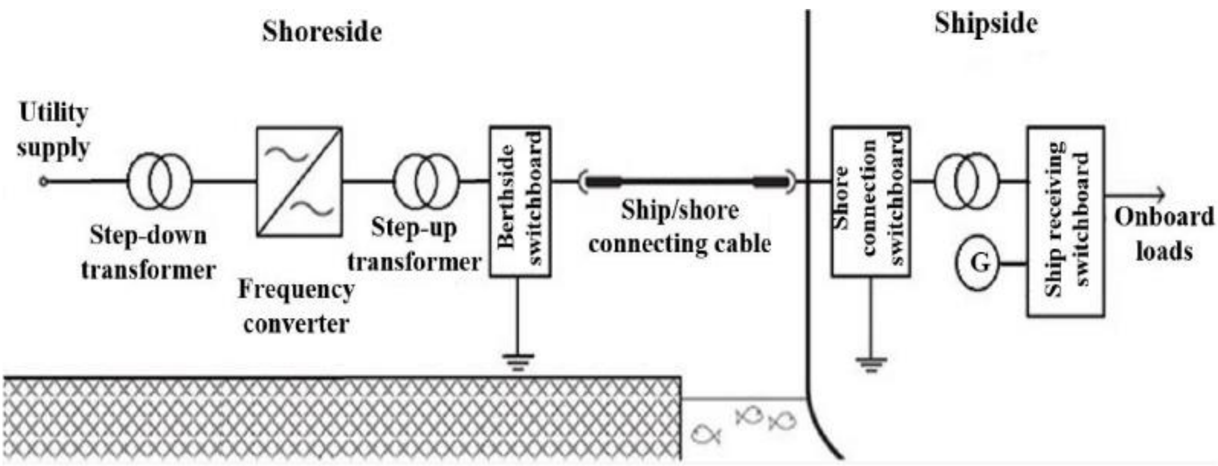


Figure 10 General requirements for equipping the system with CI technology (Edward A. Sciberras et al., 2015)

The utilization of cold ironing service in the marine transportation system has proven to be highly effective in reducing the emission of pollutants, including greenhouse gases. However, an important aspect to consider is the cost associated with implementing this service.

If the cost of equipping with the Cold Ironing (CI) system is high, it can lead to a significant increase in both financial expenses and energy supply requirements for the vessel.

Additionally, the duration of the ship's stoppage at ports, whether for cargo loading, unloading, or passenger boarding, can also impact the cost of utilizing the CI system. These factors may potentially discourage the widespread adoption of the CI service.

To encourage the use of this environmentally friendly system in the marine fleet, various solutions have been proposed. These include the implementation of auxiliary subsidies or incentives to offset the increased costs associated with CI. By introducing such measures, it is possible to foster greater adoption of the CI system within the marine industry, making it more financially viable for ship operators (Ruoli Tang et al., 2018 and Edward A. Sciberras et al., 2015).

2.2.4. The relationship between the research review and the present study

Based on the researches of (Muzaidi Othman et al., 2018), (Norbert Doerry et al., 1996) and (Abkenar et el., 2017), it can be concluded that the use of intelligent system on the ship has a significant impact on reducing environmental pollution and energy management. Also, the occurrence of fluctuations in the performance of the intelligent system has a negative effect, which should be solved by adopting effective methods. Failure to pay attention to this problem can cause that if these fluctuations occur at the time of danger, the performance of the intelligent system will not be suitable in dealing with the danger. Therefore, in the next section, researches whose performance is not affected by fluctuations (device-to-device connection) will be examined. This section indicates that the prioritization of environmental protection and energy management factors has not been done by the researchers. Also, the occurrence of fluctuations can affect the safety of travel, which causes dissatisfaction of passengers.

Based on the results of (Veerachai Gosasang et al., 2011 and Kjetil Fagerholt et al, 2009) in order to evaluate low priority variables, the squared error method was selected and regression was performed accordingly. Since the planning framework is based on optimization, in this research optimization was done based on passenger satisfaction factors and crew performance and energy sustainability.

According to the results of (Esri, 2007), (Esri, 2006), and (Jeetendre Narsoo et al., 2009), travel time is one of the main factors in passenger satisfaction. Therefore, in order to evaluate the duration of the trip in the present study, all questionnaires were completed in the ports that were equipped with the system of registering the arrival and departure of ships.

Based on the results of (Oludolapo Olanrewaju et al., 2012 and Kanellos & Guerrero et al., 2016) factors affecting economic and energy aspects were included in the form of a questionnaire so that these factors are prioritized according to the opinions of different groups. For the economic aspect, things such as the cost of equipping the ship with an intelligent system and the cost of fossil fuel, and for the energy aspect, things like clean energy and environmental pollution were considered.

According to the studies of researchers, the energy storage system and the coastal power grid, if used in an intelligent system, can be effective in reducing energy consumption and improve ship performance (Jae-Shik Park et al., 2001 and Chang, 2012 and Ruoli Tang et al., 2018). Therefore, in the current research, it was tried to use the crew and captain of the Smart ship, who were equipped with an energy storage system, to complete the questionnaire. It is clear that the opinions of the crew and the captain, who have made many trips with the Smart ship, can be more effective in prioritizing the variables. Based on the contents discussed in chapter 2, the following contents are inferred:

1. Sea voyages are one of the most important and fundamental income and economic poles of countries that have sea borders.
2. In competitive performance, countries that simultaneously develop knowledge and technology to equip the marine fleet and use more detailed planning to attract customers and manage and control are more successful.
3. Formulating coherent planning requires a complete understanding of the level of passenger satisfaction and environmental protection.
4. The use of advanced technologies and smart network can be effective in providing services to passengers.

To achieve the main goals of this research, as much as possible, the factors related to the control and management of short-term cruises should be investigated, including the safety and quality of travel, the economic aspect, and the preservation of the environment. The development of transportation in the marine fleet can be examined from various dimensions such as planning, services, supervision, and so on, each of which has its own effects for the development of transportation in the marine fleet.

Chapter 3

Case Description

3.1. Introduction

In this chapter, we commence by introducing a framework that serves as a foundation for the strategic direction of the present research. Our aim is to consistently adhere to this framework throughout the entirety of the study. The establishment of a clear framework is instrumental in determining the path towards achieving our goals effectively. Following that, we delve into the process of data mining, encompassing various subsets such as classification, evaluation, and the identification of regular patterns. These topics will be comprehensively discussed, highlighting their significance and relevance to our research.

Furthermore, it is noteworthy that the data for the current research has been collected through a questionnaire. The process of data mining plays a pivotal role in enhancing the accuracy of the results. In the upcoming section, we delve into the regression process, which holds great importance in optimizing variables and enhancing the managerial and competitive performance of the marine fleet equipped with the smart system. This process is integral to our discussion as it enables us to identify and leverage key factors that contribute to overall improvement.

Moving on, the subsequent section focuses on delineating the desired questions, effective variables, as well as the preferred seaports and data grouping. By clearly defining these elements, we establish a solid foundation for our research methodology. This step is crucial in ensuring that we gather relevant and meaningful insights.

3.2. A comprehensive framework for strategy formulation

The comprehensive framework of strategy formulation plays a vital role in developing effective strategies (Aaker, 2007 and Fred, 2011). This framework offers a range of tools and methods that are applicable to diverse types of organizations, enabling strategists to identify, evaluate, and select appropriate strategies. By leveraging this framework, strategists can enhance their decision-making processes and develop strategies that align with the organization's goals and objectives (Avinash K. Dixit et al., 2008). Additionally, the framework consists of three distinct phases, according to (Aaker, 2007 and Fred, 2011):

1. **Input phase:** The input phase is a crucial step in strategy formulation, where the necessary information for developing a strategy is identified. In this phase, the main information needed to formulate the strategy is specified. This stage includes the evaluation matrix of internal factors and the evaluation matrix of external factors. Perhaps, more knowledge that is obtained from inside and outside the fleet will lead to a change in the organization's mission, even during the strategic management process. The information that is obtained during this phase serves as a foundation for comparison and by having them in hand, the selection of different strategies can be identified and evaluated (Aaker, 2007 & Fred, 2011).

2. **Matching or comparison phase:** In this phase, based on the information gathered from the previous stages and considering the organization's mission, the main internal and external factors are aligned and harmonized. The aim is to establish a balance between them. The internal and external matrix serves as the key tool in this stage to facilitate the alignment of these factors (Aaker, 2007 & Fred, 2011).

3. **Decision-making phase:** In the final stage, a quantitative strategic matrix is utilized to assess and evaluate the strategic options identified in the previous stage. The purpose is to make objective judgments without personal bias. This matrix serves to determine the relative attractiveness of different strategies and provides an objective basis for selecting specific strategies (Aaker, 2007 & Fred, 2011).

3.3.1. Data mining process

Based on the Cross-Industry Standard Process for Data Mining standard process (CRISP-DM), known as Industry Mutual Standard Process. The data mining process can be defined based on five essential steps. These steps provide a framework for conducting effective data mining projects and achieving valuable insights (Charu C. 2015; Eduardo Rivo et al., 2012):

1. **Business knowledge:** This step involves gaining a thorough understanding of the business objectives, requirements, and domain knowledge relevant to the data mining project.
2. **Preparation of data:** In this step, the data is collected, integrated, cleaned, and transformed to ensure its quality and suitability for analysis.
3. **Modelling process:** Here, various data mining techniques and algorithms are applied to the prepared data to build models that capture patterns, relationships, and trends.
4. **Identifying the type of data:** This step involves identifying the types of data attributes, such as categorical, numerical, or text data, to determine the appropriate data mining techniques and approaches.
5. **Application and data measurement**: Finally, the developed models are applied to new data to make predictions or extract insights. The performance of the models is evaluated and measured against the project's goals and success criteria.

The standard process, as depicted in the figure below, operates in a non-linear manner, allowing for flexibility at each stage. This cyclic process enables the opportunity to backtrack and repeat steps until the optimal outcome is achieved in data mining (Nick Hotz, 2023 and Pete Chapman et al.,1999).

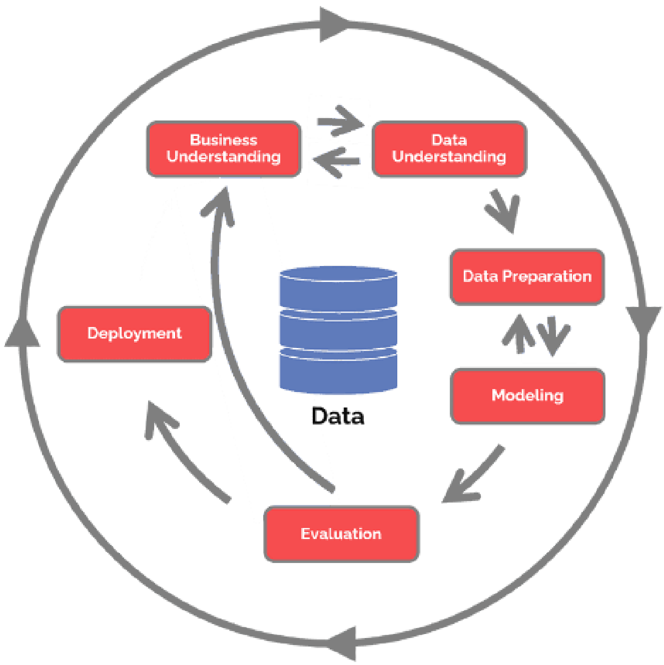


Figure 11 Non-linear standard model of data mining (Nick Hotz, 2023)

3.3.2. Various functions of data mining

By employing the process of data mining, valuable patterns within the data are identified autonomously, without requiring user intervention. Subsequently, this information is relayed to experts, enabling them to make informed decisions based on the identified patterns. This highlights the significance of data mining in extracting meaningful insights and empowering decision-making processes (Suh, 2012 and Aggarwal et al., 2015).

Among the different functions encompassed by the data mining process are the following:

1. Classification
2. Evaluation and estimate
3. Forecast
4. Classification of similarity
5. Clustering process
6. Explanation and indexing

Classification

The data classification process involves sorting and categorizing the relevant data into different classes. During this process, a hypothetical model is developed based on distributed data, and this initial model is subsequently utilized to classify all new data. Ultimately, the obtained classification data can be assigned to specific classes using the proposed model. This iterative approach to data classification ensures efficient organization and categorization of data, facilitating effective analysis and decision-making (Aggarwal et al., 2015).

Classification serves as a valuable approach for predicting discrete values. During the classification process, existing objects are sorted into distinct classes based on their on their distinguishing characteristics, thereby introduced as a model. Subsequently, by considering the characteristics of each class, new objects can be assigned to the appropriate class, allowing their level and type to be determined. In the classification process, the new model is developed based on the data training process, and the obtained model can be displayed using various advanced techniques, including knowledge of neural networks, decision tree algorithm, and classification process, can be employed to visualize and refine the resulting model (Pete Chapma et al.,1999).

Evaluation and estimation

In estimation, the goal is to determine the value of an unknown output parameter. Typically, estimation problems involve numerical output parameters rather than categorical ones. Hence, analogical elements need to be converted into a numerical state, such as transforming "yes" and "no" into 0 and 1. The estimation process is particularly useful when the actual parameter values are unknown to us. Data may have been collected under varying and possibly inadequate conditions, prompting experts to utilize the estimation process. Regression models and neural networks are suitable data mining techniques that can effectively perform the estimation process, providing valuable insights and predictions (Pete Chapman et al, 1999).

Forecast

The purpose of the forecasting process is to determine the output based on the existing pattern and behaviour. In the forecasting process, the output variable and its corresponding result are obtained based on the available information derived from the data. The output variables in forecasting can take the form of numerical or analogical values. This technique holds significant importance among various data mining methods, as it enables the prediction of future outcomes. Many data mining monitoring techniques, which are suitable for tasks such as data classification and estimation, incorporate some form of prediction process (Pete Chapman et al.,1999).

Classification of similarity

The process of similarity classification is directed towards identifying elements that are commonly grouped or categorized together. It focuses on analyzing market baskets, which consist of goods commonly selected together during a purchase. By examining the purchasing patterns of buyers in a store, this method allows for determining the associations and arrangements of various products. Experts consider similarity classification as a straightforward approach for generating rules based on data (Pete Chapman et al, 1999).

Clustering process

Clustering is the process of dividing a group of data and different objects into subclasses. Clustering consists of a series of similar data that behave as a single and identical group. In other words, clustering is the same as classification, but with the distinction that the classes are not predetermined or defined in advance. The process of grouping the data is unsupervised, allowing for the identification of natural patterns and structures within the dataset (Aggarwal et al., 2014)

In clustering, the principle of maximum and minimum similarity between members of individual classes is used to perform the classification process. In the clustering process, the clusters are set so that the objects inside each cluster have the most similarity with each other. Each cluster is a class from which the rules are derived (Pete Chapman et al., 1999).

Explanation and indexing

When data mining is employed to uncover the underlying rules governing a specific database, it requires specialized knowledge. Without familiarity with the data, the process can be time-consuming and necessitate human intervention and expertise to comprehend the relationships between different data elements. However, indexing provides a more efficient approach to deduce such information. Description and indexing tasks can be accomplished using techniques like decision trees, dependency rules, and clustering, which facilitate the extraction of meaningful insights from the data (Pete Chapman et al., 1999).

3.4. Regression

Regression analysis is a valuable statistical technique used to examine the relationship between variables and make predictions based on logical associations. By identifying a logical relationship between variables, regression analysis becomes an effective tool for predicting the values of variables of interest. In regression analysis, the number of independent variables can be more than 1, but the number of dependent variables must be equal to 1.

By performing regression analysis, only the governing relationships between a group of independent variables and dependent variables are extracted. Extracting the relationships and the ruling pattern between independent and dependent variables in forecasting, the relationship between two variables has a significant role in determining the outcome, and extracting the relationships and patterns allows for a better understanding of the impact and influence between the variables. (Quiroga, 1986).

3.5. Different types of input data

The purpose of the data mining process is to build models. The models always take a certain group of data (input) and produce the desired output variables based on the defined algorithm. The model set contains information that is used to describe and build the model. After building the model, they must be applied to the desired information, which is referred to as the ranking stage. The model set consists of three parts:

1. **Training set:** The training set refers to a specific portion of the available data that is utilized during the model training process. This set of data is used to initialize the desired model and establish its structure.

2. **Test set:** The test set is another subset of the available data that is utilized to assess and evaluate the accuracy of the trained model. This set of data contains known output values, allowing for a comparison between the model's predicted output and the actual output. By applying the test set to the trained model, its performance can be evaluated, providing insights into the accuracy and effectiveness of the model.

1. **Validation set:** The validation set is utilized to determine and evaluate the performance of the model on new input data. By testing the model on the validation set, its performance can be measured and analyzed, providing valuable insights into its effectiveness and reliability (Trevor Hastie et al., 2001).

3.6. Frequency distribution of data

The purpose of examining and analyzing external factors is to identify potential opportunities that can be exploited to enhance and improve the system.

While it may be of less significance to compile an exhaustive list of every factor that can potentially impact the organization, the priority lies in identifying the key variables that have a positive influence on system performance. The focus is on determining the primary variables that contribute to enhancing the overall efficiency of the system, rather than exhaustively listing every possible factor that can affect the organization. The classification of external forces, as presented below, helps in organizing and understanding the influential factors that affect the organization's operations (Aaker, 2007)

1) Economic forces
2) Social, cultural, ecological, and environmental forces
3) Political, governmental, and legal forces
4) Technological forces
5) Competitive forces

Changes in external forces have a direct impact on the demand for services, leading to fluctuations in demand.

General environment: Encompasses a set of factors that influence the marine fleet and are beyond the organization's control. These factors can include:

1. Economic factors
2. Sociocultural factors
3. Technological factors
4. Legal political factors
5. Global factors

Expert environment: Refers to the stakeholders with whom the fleet regularly interacts. (Aaker, 2007). The key stakeholders in the expert environment include:

1) **Customers:** These are the individuals or organizations who utilize the services provided by the fleet. Understanding their needs, preferences, and expectations is crucial for delivering satisfactory services and maintaining customer satisfaction.

2) **Suppliers:** Suppliers are the entities that provide essential resources and materials required by the fleet to operate efficiently. Building and maintaining strong relationships with reliable suppliers is vital for ensuring a steady supply chain and minimizing disruptions.

3) **Existing competitors:** These are the organizations that operate in the same industry and offer similar services. Monitoring and analyzing the strategies and actions of existing competitors is essential for staying competitive and identifying opportunities for differentiation.

4) **Potential competitors (new entrants):** These are new organizations that may enter the market and pose a potential threat to the fleet's market share. Keeping an eye on emerging competitors and their entry barriers is crucial for adapting strategies and maintaining a competitive edge.

5) **Indirect competitors (substitutes):** Indirect competitors refer to alternative services or products that fulfil similar customer needs. Recognizing and evaluating indirect competitors is important to understand market dynamics and identify potential threats or opportunities.

3.7. Evaluation of the Data Collected from the Questionnaire

In this research, data collection was conducted through a questionnaire, encompassing three key classifications: passenger satisfaction, ship crew performance, and pollution have been considered as the main factors. These classifications were identified as influential factors within the interconnected network of the marine fleet. The dataset comprised a total of 24 data points, which were obtained from various sources including passengers, captains, crew members, and inspectors.

3.7.1 The age range of the respondents

In the current research, we designed a questionnaire that incorporated variables impacting the triple factors. This questionnaire was administered to individuals from four distinct groups: passengers, crews, inspectors, and captains.When analyzing the age demographics of the participants who responded to the questionnaire, we found that the inspector and captain groups had individuals ranging in age from 35 to 55 years. The ship crew group consisted of individuals between the ages of 30 and 45 years. As for the passenger group, the age range varied from 25 to 60 years.

3.7.2 Geographical Scope of Questionnaire Distribution

The geographical range for the distribution of questionnaires was selected based on the criteria, which are monitoring the entry and exit of the ship and the energy storage system, that were examined in Chapter 2. Also, our view was upon somehow global, meaning that it was concerned to look at other places in the world and not only one place (such as Norway). Some ships in the three ports of Hamburg in Germany, Shanghai in China, and Molde in Norway were among the ports equipped with intelligent systems that were chosen to collect the data for this research.

3.7.3 Effective variables based on Triple Factors

In these questions, the variables that were examined were used to define the factors influencing satisfaction and sustainability of energy and crew performance. The main purpose of posing these questions was to explore the perspectives of different groups regarding the impact of deploying a smart network in the marine fleet. When completing the questionnaire, one of the criteria was to consider previous experience in traveling by a smart ship as part of the desired variables.

This enabled us to evaluate all the relevant factors simultaneously when predicting the variables. The table below presents the specific questions that were asked in this research to the four groups: passengers, ship crew, inspector, and captain.

Table 1 Questions based on the triple factors

E1	**How does the implementation of an intelligent system impact the performance of the ship's crew?**
E2	**Does the deployment of the intelligent system have an effect on ensuring that the crew perform their duties according to the global rules and standards of the marine fleet?**
P1	**Does the intelligent system have an impact on reducing fossil fuel consumption and promoting optimal energy usage, such as the utilization of solar and wind energy?**
E3	**Does the intelligent system in the event of danger and accidents have an effect in helping the crew to deal with the danger?**
S1	**Does the intelligent system have an effect on the analysis of dangerous and high-risk factors?**
S2	**Is the intelligent system effective in preventing time wasted when passengers board the ship?**
P2	**Does the intelligent system have an effect in predicting the shortest sea route (in order to reduce fuel consumption and travel time)?**
S3	**Does the intelligent system contribute to enhancing the safety of passengers?**
E4	**Does the intelligent system demonstrate effectiveness in ship control and management?**
E5	**Does the intelligent system impact information exchange with the management center and timely notification in case of danger?**
P3	**Does the intelligent system have an effect in predicting adverse weather conditions particularly in relation to utilizing wind and solar energy?**
S4	**Does the intelligent system contribute to enhancing travel quality and passenger satisfaction?**
S5	**How effective is the establishment of the intelligent system in reducing the cost of sea travel?**
E6	**Does the intelligent monitoring system impact marine traffic management in seaports?**

P4	**Does the intelligent system have an effect on choosing the best time for travel according to peak energy consumption?**
E7	**Does the intelligent system have an effect in controlling the situation and selecting safe conditions during the trip in case of a delay in the cruise?**
P5	**Does the establishment of an intelligent network contribute to environment preserving and pollution reducing?**
S6	**Is the intelligent system effective in transmitting passengers' complaints and critical comments to the marine fleet officials?**
E8	**Is the intelligent monitoring system successful in notifying the ship in case of a technical failure?**
P6	**Is the launch of the intelligent ship system beneficial for the marine fleet in the long run by reducing the cost of fuel consumption and not wasting travel time?**
E9	**If there is a technical defect in the intelligent system, will the experts of the marine fleet succeed in correcting the defect in time?**
E10	**Does the level of knowledge of the marine fleet crew have an effect on the correct and principled management of the intelligent monitoring system in the marine fleet?**
S7	**Does the deployment of intelligent monitoring system in the marine fleet have a positive effect on passengers?**
E11	**Does the establishment of the intelligent system have a negative effect on the view of the ship's crew on the issue of unemployment?**

3.7.4. Stages of Evaluation of the Data Collected from the Questionnaire

In this phase of the research, we conducted the data mining process on the data collected from the questionnaires, aligning it with the specified criteria. The primary objective of employing data mining in this study is:

Identification of incomplete or duplicate data:

In order to increase the accuracy of the results, the relevant data identification process was carried out.

In this research, the data obtained from the questionnaire was completed by 4 groups including passengers, captain, crew and inspector. After collecting the questionnaires, some passengers could not answer some of the questions. It was also observed that some passengers had chosen 2 options for the same question. By doing the data mining process, these items were corrected.

The collected questionnaires were equal to 100, which were collected from the three ports of Shanghai Pin, Hamburg, Germany and Molde port. In order to find the relevant pattern between the collected data, several patterns were considered, and finally one of the patterns was able to present a suitable pattern.

The questions that received an excellent grade from the passengers were placed in group 1, the questions that received a good grade were placed in group 2, the questions that received an average grade were placed in group 3, and the questions that received a poor grade were placed in group 4.

The questions that received an excellent grade from the examiners were placed in group 5, the questions that received a good grade were placed in group 6, the questions that received an average grade were placed in group 7, and the questions that received a poor grade were placed in group 8.

The questions that received an excellent score from the captains were placed in group 9, the questions that received a good score were placed in group 10, the questions that received an average score were placed in group 11, and the questions that received a poor score were placed in group 12.

Based on the passengers' evaluations, the questions that received an excellent grade were categorized into group 13, while questions that received a good grade were placed in group 14. Questions that garnered an average grade were assigned to group 15, and those that received a poor grade were allocated to group 16.

5 passengers did not answer 2 questions, 3 passengers did not answer 3 questions, 1 passenger did not answer 4 questions, and 1 did not answer 5 questions. The unanswered questions were placed in groups 17 to 20 respectively.

The results of data mining and grouping of participants' answers are presented in Figures 12 to 15.

In the questionnaire, which was used to complete it from different groups of people with different age ranges, relevant symptoms were defined to classify the variables. Questions pertaining to passenger satisfaction category were identified with labels E4, P3, P4, E8, P6, E5, and P2. The questions related to the performance factor of the crew and the captain were marked with E1, E1, S3, E7, P5, E9, S1, S5, S7, E11 and E6. Questions related to the energy sustainability factor were distinguished by the labels P1, S4, S6, E3, S2 and E10. To evaluate the answer of each group, passenger group No. 1, inspector group No. 2, captain group No. 3, and crew group No. 4 were determined.

The perspectives of different groups who participated in the questionnaire are presented in Figures 12 to 15. According to Figure 12, it is evident that, on average, 30% of the passenger's expressed satisfaction with the remarkable level of travel provided by smart ships. Furthermore, over 80% of the passengers, on average, rated the quality of travel with smart ships as good. According to the provided figure, it is evident that passengers rated question P2, which explores the "impact of deploying an intelligent monitoring system in the marine fleet on passengers", was able to get the excellent.

Figure 12 Frequency distribution of data completed by passengers

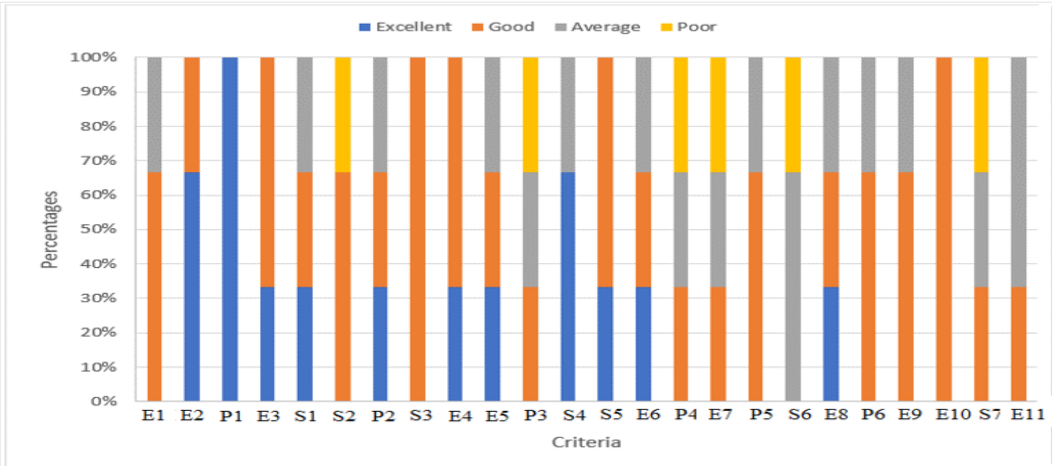


Figure 13 Frequency distribution of data completed by inspector

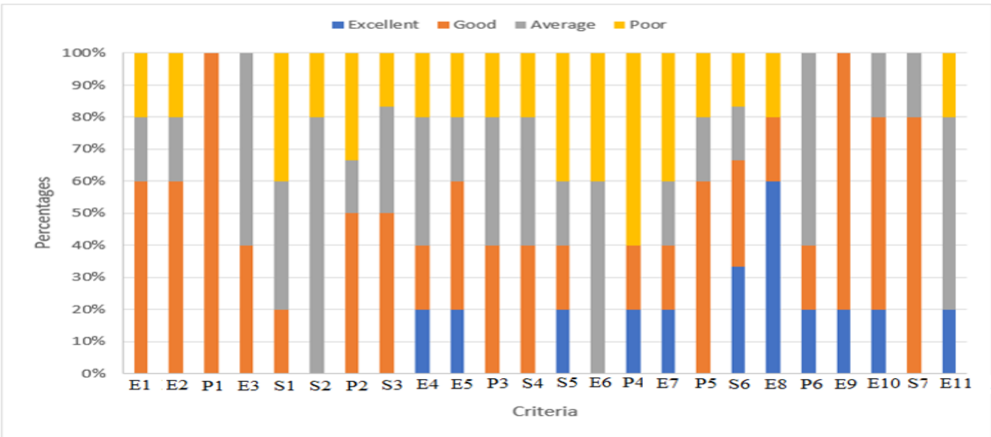


Figure 14 Frequency distribution of data completed by Captain

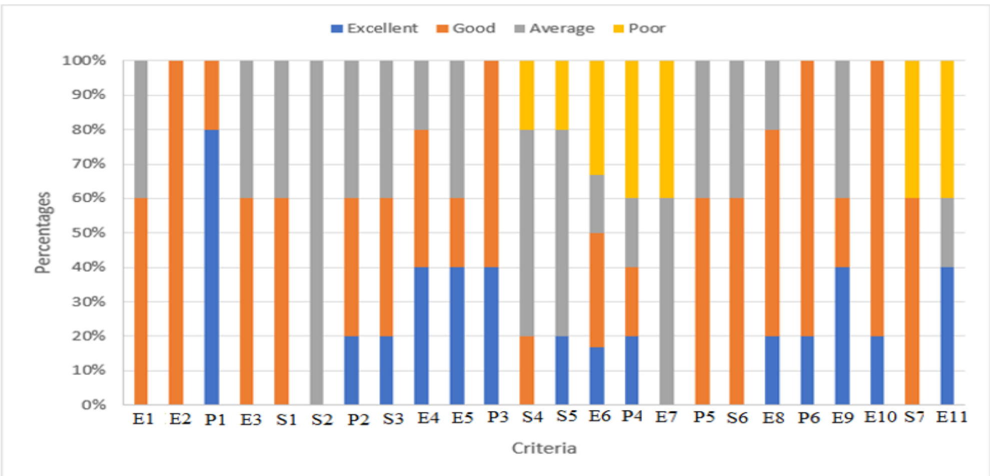


Figure 15 Frequency distribution of data completed by crew

According to Figure 13, it can be seen that, on average, 60% of the inspectors evaluated the quality of traveling by smart ship as excellent and good. Additionally, based on the data presented in Figure 13, it is evident that the inspectors' opinion indicates an excellent score for question P1, which addresses the topic of "whether the intelligent system has an impact on reducing fossil fuel consumption and optimizing the use of solar and wind energy?"

Based on the information provided in Figure 14, it is apparent that approximately 40% of the captains have rated the quality of traveling with a smart ship as higher than good. Furthermore, according to the feedback from the captains in Figure 14, question P1, which focuses on "the impact of the intelligent system on reducing fossil fuel consumption and optimal consumption using solar and wind energy", has received a good level of score.

Based on the information provided in Figure 15, it is evident that, on average, 60% of the crew members on the smart ship have rated the quality of traveling with the smart ship higher than good. Additionally, according to the feedback from the crew members in Figure 15 the question regarding the impact of deploying the intelligent system on ensuring that the crew performs their duties according to the global rules and standards of the marine fleet has received a full score, indicating a good level.

3.8. Data classification in SPSS software

In this part, we define all the data obtained from the questionnaires completed by four different groups in the software (Figure 16). For this research, the questions were proposed with consideration for three main factors: energy sustainability, ship crew performance and passenger satisfaction. These factors were taken into account to answer the questions of the smart ship travel experience criteria for each group.

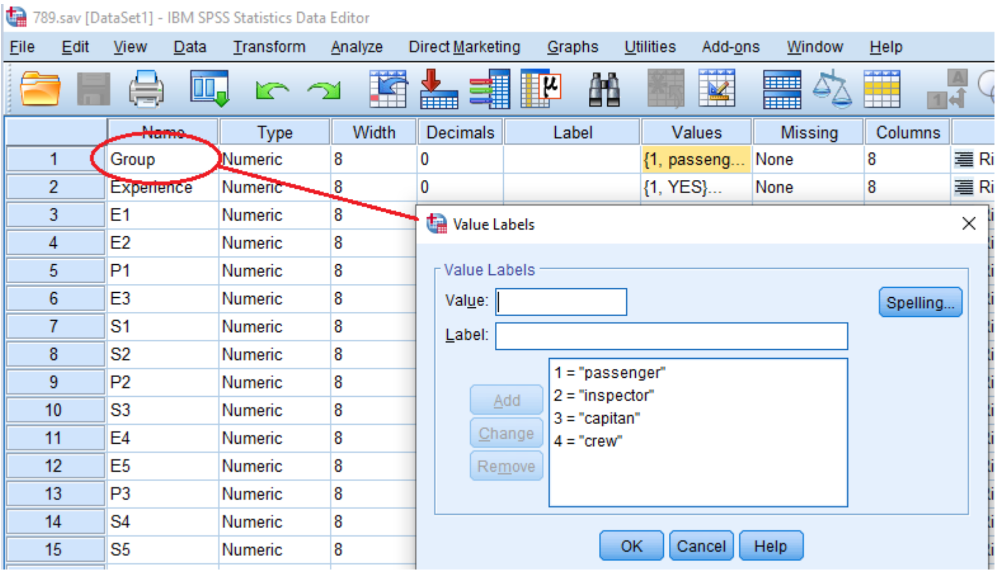


Figure 96 The process of defining each of the target groups in the research

In this section, the definition of the criteria for previous experience in traveling by intelligent ship has been discussed, as shown in Figure 17. For each of the target groups who completed the questionnaire, a designation of either 1 or 2 was considered based on whether they had previous experience in traveling by an intelligent ship. It is worth noting that three groups, namely the captain, crew, and inspector, had prior experience in traveling with an intelligent ship, while only a few passengers were experiencing it for the first time.

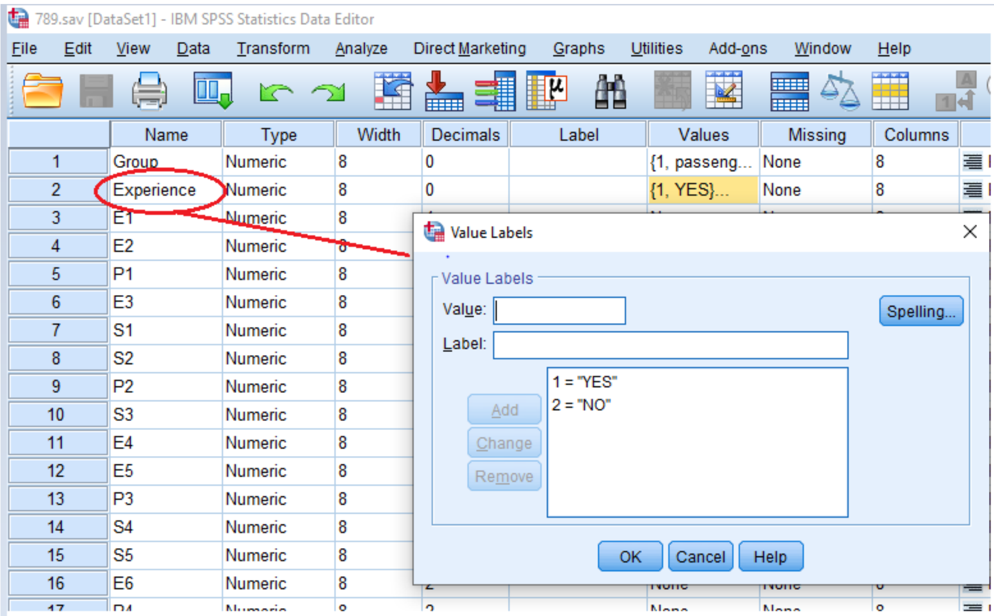
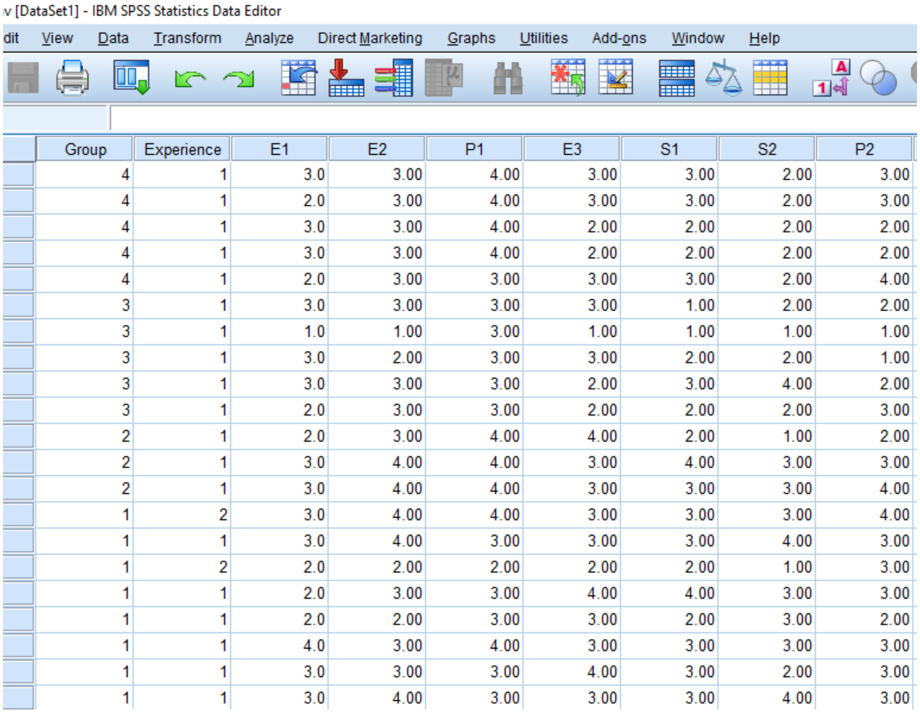


Figure 17 The process of defining the criteria of experience for each of the target groups

After all all data and information have been st up, Figure 18 is provided and displays the entirety of the dataset.



Group	Experience	E1	E2	P1	E3	S1	S2	P2
4	1	3.0	3.00	4.00	3.00	3.00	2.00	3.00
4	1	2.0	3.00	4.00	3.00	3.00	2.00	3.00
4	1	3.0	3.00	4.00	2.00	2.00	2.00	2.00
4	1	3.0	3.00	4.00	2.00	2.00	2.00	2.00
4	1	2.0	3.00	3.00	3.00	3.00	2.00	4.00
3	1	3.0	3.00	3.00	3.00	1.00	2.00	2.00
3	1	1.0	1.00	3.00	1.00	1.00	1.00	1.00
3	1	3.0	2.00	3.00	3.00	2.00	2.00	1.00
3	1	3.0	3.00	3.00	2.00	3.00	4.00	2.00
3	1	2.0	3.00	3.00	2.00	2.00	2.00	3.00
2	1	2.0	3.00	4.00	4.00	2.00	1.00	2.00
2	1	3.0	4.00	4.00	3.00	4.00	3.00	3.00
2	1	3.0	4.00	4.00	3.00	3.00	3.00	4.00
1	2	3.0	4.00	4.00	3.00	3.00	3.00	4.00
1	1	3.0	4.00	3.00	3.00	3.00	4.00	3.00
1	2	2.0	2.00	2.00	2.00	2.00	1.00	3.00
1	1	2.0	3.00	3.00	4.00	4.00	3.00	3.00
1	1	2.0	2.00	3.00	3.00	2.00	3.00	2.00
1	1	4.0	3.00	4.00	3.00	3.00	3.00	3.00
1	1	3.0	3.00	3.00	4.00	3.00	2.00	3.00
1	1	3.0	4.00	3.00	3.00	3.00	4.00	3.00

Figure 18 View of definition data for different variables

The table below illustrates the categorization of research questions based on 3 factors: passenger satisfaction, crew performance, and energy sustainability. The first layer comprises 24 variables that were identified in accordance with these three factors. The previous section provides an explanation on how these variables were assigned to their respective triple factors. Additionally, the third layer consists of two dependent variables, namely group and experience.

Table 2 Information of different layers of the model

First layer	Various factors	1	E1
		2	E2
		3	P1
		4	S3
		5	E4
		6	P3
		7	S4
		8	P4
		9	E7
		10	P5
		11	S6
		12	E8
		13	P6
		14	E9
		15	E3
		16	S1
		17	S2
		18	E5
		19	S5
		20	E10
		21	S7
		22	E11
		23	P2
		24	E6
	Number of allocated units		87
Second Layer(s)	The number of allocated layers		1
	Number of allocated units		12
	Definitional activation function type		Hyperbolic tangent
Third Layer	Number of dependent variables	1	Group
	Number of desired variables	2	Experience
	Number of allocated units		6
	Definitional activation function type		SoftMax
	Type of error determination function		Cross-entropy

The objective of this section is to compare models based on the percentage of different tests and determine the optimal test percentage for selecting models that yield the highest level of prediction accuracy. The selection of various percentages for training, testing, and hidden layers for samples can influence the magnitude of calculation errors. In this study, different percentages were considered for the aforementioned 3 stages.

Ultimately, 13 samples were chosen for the training stage, while during the testing phase, the number of samples selected was equivalent to 17.6% of the total sample size. The table below provides the detailed information regarding these percentages.

Table 3 Values Specific to Testing and training

		Number of samples (N)	Percent
phase	Amount and percentage of holdout	1	5.9%
	Amount and percentage of testing	3	17.6%
	Amount and percentage of training	13	76.5%
Amount excluded		4	-
Percentage validity of the result		17	100.0%
Final total		21	-

The proposed model is developed based on all data and input parameters by IBM SPSS Modeler software. That is, the proposed model is developed based on various values of hidden layers, and then the appropriate value that leads to the selection of a model with the least amount of error is selected as a criterion.

In the current research, the model employed hidden and output layers with values of 1 and 2, respectively. A crucial step in the IBM SPSS Modeler software is determining the importance of input parameters, which is done through supplementary questionnaires. The importance of these input parameters indicates their influence on predicting the output parameter, with values ranging from 0 to 1. The closer the value is to 1, the more significant the desired input parameter is in predicting the output parameter.

The table below displays the error values for the training and testing results. Based on the table 4, it is evident that the amount of prediction error for the three stages of testing, training, and the hidden layer for the two variables of experience and group is equal to 0.

Table 4 Error values for the proposed model

Training	Value of computational entropy error		.015
	Incorrect Forecasts (average percentage)		0.0%
	Incorrect Forecasts (class dependents)	Group	0.0%
		Experience	0.0%
	Stop rule		Sequential step without reduction in error value
Testing	Value of computational entropy error		.676
	Incorrect Forecasts (average percentage)		0.0%
	Incorrect Forecasts (class dependents)	Group	0.0%
		Experience	0.0%
Holdout	Incorrect Forecasts (average percentage)		0.0%
	Incorrect Forecasts (class dependents)	Group	0.0%
		Experience	0.0%

Chapter 4

Data and method

4.1. Introduction

In this chapter, the collected data is thoroughly analyzed, and subsequently, the variables that have an impact on the three factors are prioritized based on the results of the optimization process. The collected data and information are categorized, evaluated, and processed, taking into consideration the opinions of different groups.

A questionnaire was employed to gather the necessary data for this research. Through data evaluation, a model is presented to establish the relationship between the collected data and facilitate accurate data predictions. The data analysis process encompasses three main steps:

1. Preparation and collection of data
2. Evaluation of the pattern among all the variables
3. Evaluation of the accuracy of the results compared to different criteria

In this research, the obtained data, which is based on the opinions of different groups such as passengers, ship crew, captain and inspector, is trained and tested using neural network. Subsequently, a model is developed to predict the data accurately. IBM SPSS Modeler software is employed for analyzing the collected data. The optimization process is then conducted to assess the impact of eliminating variables with low impact or significance on the model. Finally, the variables influencing the three factors are prioritized, allowing the marine fleet to concentrate on more critical aspects and important priorities to enhance their managerial and competitive performance.

4.2. Data and questionnaire

The data required for this research was collected through qualitative methods, gathering insights from various groups such as passengers, ship crew, inspectors, and captains. The research questionnaire encompassed three key factors: energy sustainability, passenger satisfaction, and crew and captain performance. Questions related to the energy coefficient were highlighted in yellow, those related to passenger satisfaction were marked in blue, and the ones concerning crew performance were indicated in gray in Table 5. When formulating these questions, a comprehensive range of variables influencing these factors were considered, aiming to incorporate diverse opinions and prioritize the influential factors effectively.

Table 5 Categorized and grouped questions based on three factors

1. Does the establishment of the intelligent system affect the performance of the ship's crew?
2. Does the deployment of the intelligent system have an effect on ensuring that the crew perform their duties according to the global rules and standards of the marine fleet?
3. Does the intelligent system have an effect on reducing fossil fuel consumption and optimal consumption (use of solar and wind energy)?
4. Does the intelligent system in the event of danger and accidents have an effect in helping the crew to deal with the danger?
5. Does the intelligent system have an effect on the analysis of dangerous and high-risk factors?
6. Is the intelligent system effective in preventing time wasted when passengers board the ship?

7. Does the intelligent system have an effect in predicting the shortest sea route (in order to reduce fuel consumption and travel time)?
8. Does the intelligent system have an effect on the safety of passengers?
9. Is the intelligent system effective in ship control and management?
10. Does the intelligent system have an effect on information exchange with the management center and timely notification in case of danger?
11. Does the intelligent system have an effect in predicting adverse weather conditions (with regard to the use of wind and solar energy)?
12. Does the intelligent system have an effect on the improvement of travel quality and passenger satisfaction?
13. How effective is the establishment of the intelligent system in reducing the cost of sea travel?
14. Does the intelligent monitoring system have an effect on marine traffic management in seaports?
15. Does the intelligent system have an effect on choosing the best time for travel (according to peak energy consumption)?
16. Does the intelligent system have an effect in controlling the situation and selecting safe conditions during the trip in case of a delay in the cruise?
17. Does the establishment of an intelligent network have an effect on preserving the environment and reducing pollution?
18. Is the intelligent system effective in sending passengers' complaints and critical comments to the marine fleet officials?
19. Is the intelligent monitoring system successful in notifying the ship in case of a technical failure?
20. Is the launch of the intelligent ship system beneficial for the marine fleet in the long run by reducing the cost of fuel consumption and not wasting travel time?
21. If there is a technical defect in the intelligent system, will the experts of the marine fleet succeed in correcting the defect in time?
22. Does the level of knowledge of the marine fleet crew have an effect on the correct and principled management of the intelligent monitoring system in the marine fleet?
23. Does the deployment of intelligent monitoring system in the marine fleet have a positive effect on passengers?

24. Does the establishment of the intelligent system have a negative effect on the view of the ship's crew on the issue of unemployment?

4.3. Proposed research method

In this part, we have conducted an investigation into the impact of desired variables on the triple factors. By utilizing the materials discussed in the previous chapters and analyzing the collected data, we aimed to determine and analyze the components that serve as evaluation criteria for these triple factors. This analysis was based on information obtained from questionnaires completed by various groups, aligning with the objectives of our research.

This part focuses on investigating the probabilistic function predicted by the proposed network for the experience criterion. According to the information obtained from the data collected based on experience criteria, input and output and hidden layers were considered for the data. Finally, using the training process, the pattern between the data was predicted with the least possible error.

Table 6 Predicted results for the experience criterion

Layer	Observed	Forecasted		
		Yes	No	Correct (Percent)
Training	Yes	11	0	100.0%
	No	0	2	100.0%
	Overall Percent	84.6%	15.4%	100.0%
Testing	Yes	3	0	100.0%
	No	0	0	0.0%
	Overall Percent	100.0%	0.0%	100.0%
Holdout	Yes	1	0	100.0%
	No	0	0	0.0%
	Overall Percent	100.0%	0.0%	100.0%

Table 6 provides the forecast percentages for various groups, including passengers, ship crew, captain, and inspector, across different layers. Based on the Table 6, it can be observed that the accuracy of predicting the variable related to having prior experience in traveling with a smart ship (yes) is 100% in the training, testing, and hidden layers. This indicates that the model successfully predicted 11, 3, and 1 samples in the training, testing, and hidden layers, respectively.

Furthermore, the training layer achieved a remarkable prediction accuracy rate of 100% for the variable "no previous experience in traveling with a smart ship" (denoted as "no"). This result was obtained based on two samples per prediction.

4.3.1 Predictions for different groups

In this section, we explore the probabilistic function generated by the proposed neural network for various groups, such as passengers, captains, ship crew, and inspectors. To accomplish this, we initially classify the opinions of these distinct groups into different levels, namely excellent, good, average, and poor, based on the information gathered from the questionnaires. Subsequently, we utilize the training process to predict the frequency of data within each category. The resulting predictions, along with the model's error values and accuracy, are documented in Table 7.

Table 7 shows partial and overall forecast percentages for different groups (crew, passengers, captain and inspector) for different layers of training and testing and hidden. According to the table 7, the prediction accuracy percentage for the passenger group is 100% in the training, test, and hidden layers. This corresponds to the prediction of 5, 1, and 1 samples in the training, test, and hidden layers, respectively.

In the captain group, the prediction accuracy percentage is 100% in both the training and test layers. Specifically, 2 samples were accurately predicted in the training layer, while 1 sample was accurately predicted in the test layer. Similarly, for the ship crew group, the prediction accuracy percentage was also 100% in both the training and testing layers. In the training layer, 4 samples were predicted accurately, and in the testing layer, 1 sample was accurately predicted.

Further, the ship crew group demonstrated a prediction accuracy percentage of 100% in both the training and testing layers. This was achieved through accurate predictions of 4 samples in the training layer and 1 sample in the testing layer. These impressive results highlight the high accuracy of the proposed neural network in predicting the variables.

Table 7 Predicted results for different groups

Sample	Observed	Predicted				
		passenger	inspector	Captain	crew	Percent Correct
Training	Passenger	5	0	0	0	100.0%
	Inspector	0	2	0	0	100.0%
	Captain	0	0	2	0	100.0%
	Crew	0	0	0	4	100.0%
	Overall Percent	38.5%	15.4%	15.4%	30.8%	100.0%
Testing	Passenger	1	0	0	0	100.0%
	Inspector	0	0	0	0	0.0%
	Captain	0	0	1	0	100.0%
	Crew	0	0	0	1	100.0%
	Overall Percent	33.3%	0.0%	33.3%	33.3%	100.0%
Holdout	Passenger	1	0	0	0	100.0%
	Inspector	0	0	0	0	0.0%
	Captain	0	0	0	0	0.0%
	Crew	0	0	0	0	0.0%
	Overall Percent	100.0%	0.0%	0.0%	0.0%	100.0%

4.3.2 Evaluation of forecasts and triple factors

In this part, we have conducted an investigation and evaluation of the accuracy of the proposed model in predicting various factors. The results reveal that the overall percentage of correct predictions for both the testing and training sections reached an impressive 100%. This outstanding accuracy serves as evidence of the effectiveness and reliability of the proposed neural network in accurately predicting the variables

IBM SPSS Modeler (Clementine) offers several advantages, one of which is its ability to perform graph analysis, particularly in relation to ranking the input variables and generating accuracy graphs for the proposed model. The figure below illustrates both the significance and ranking of the input variables in the proposed model, along with the accuracy chart.

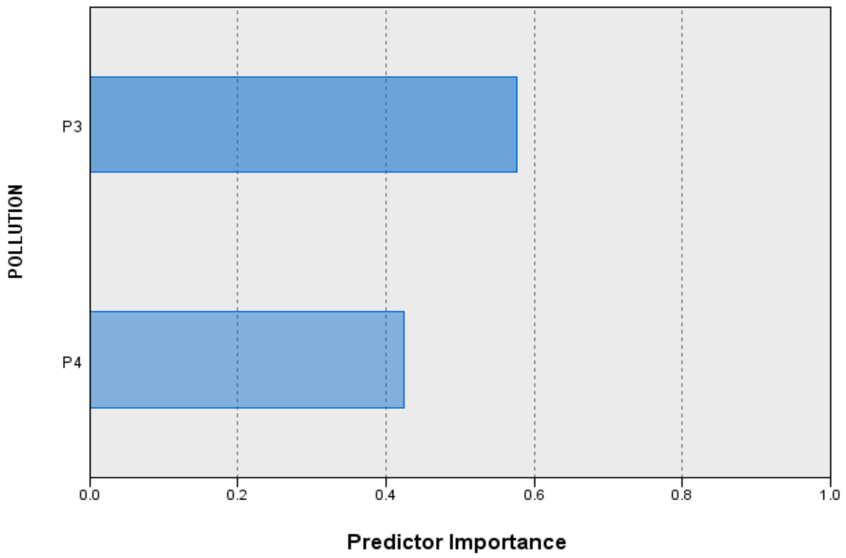


Figure 19 The most important variable affecting the pollution factor

According to Figure 19, it is evident that variable P3 holds the highest predictive significance among the variables influencing pollution. The topic of this variable was related to minimizing passenger time wastage during the ship boarding process.

Variable P3 aimed to asses the effectiveness of:

“Does the intelligent system effectively prevent time wastage during the boarding process of passengers on the ship?”

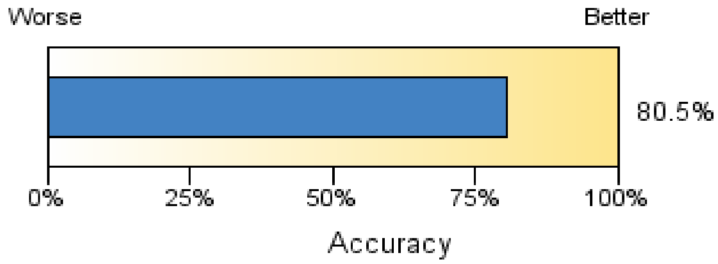


Figure 20 Prediction accuracy in evaluating pollution factor

According to the prediction results of the neural network (Figure 20), it can be seen that the modelling accuracy is equal to 80.5%, which indicates the high accuracy of the proposed neural network. Figure 21 illustrates the outcomes obtained for the variables that have the most significant impact on the passenger satisfaction factor.

According to the prediction results depicted in Figure 21 from the neural network, it is evident that variable S4 holds the utmost importance among the variables affecting the passenger satisfaction factor. This variable is associated with predicting the shortest route and reducing travel distance.

Variable S4 aimed to assess the impact of:

“Is the intelligent system effective in predicting the shortest sea route, thereby reducing fuel consumption and travel time?”

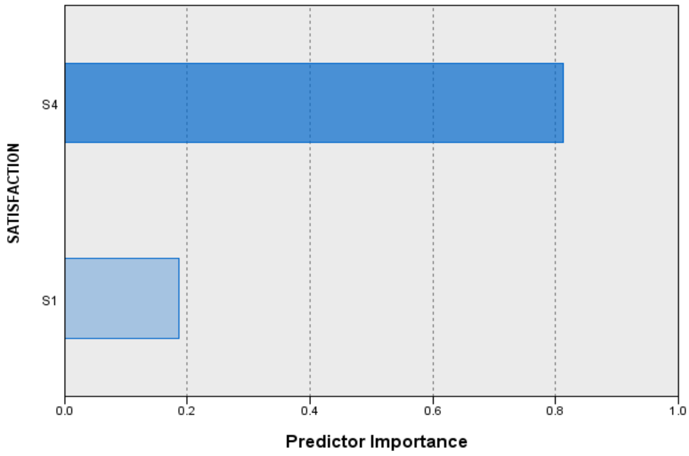


Figure 21 The most important variable affecting the passenger satisfaction factor

According to Figure 22, it is evident that the modeling accuracy in predicting the variables that affect the passenger satisfaction factor stands at 85.4%.

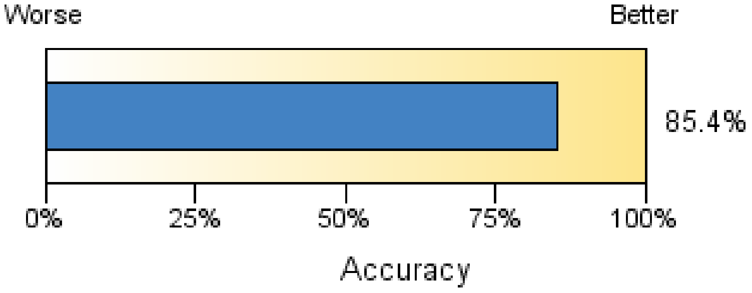


Figure 22 Prediction accuracy in evaluating satisfaction factor

Figure 23 presents the results obtained for the most impactful variable on the ship crew performance factor.

Based on the prediction results shown in Figure 23 from the neural network, it is apparent that variable E10 holds the highest significance among the variables influencing the crew's performance factor. This variable is associated with reducing fuel consumption and minimizing travel time wastage.

The variable E10 aimed to assess the long-term benefits of:

"Does the implementation of the intelligent ship system yield long-term benefits for the marine fleet by reducing fuel consumption costs and minimizing travel time wastage?"

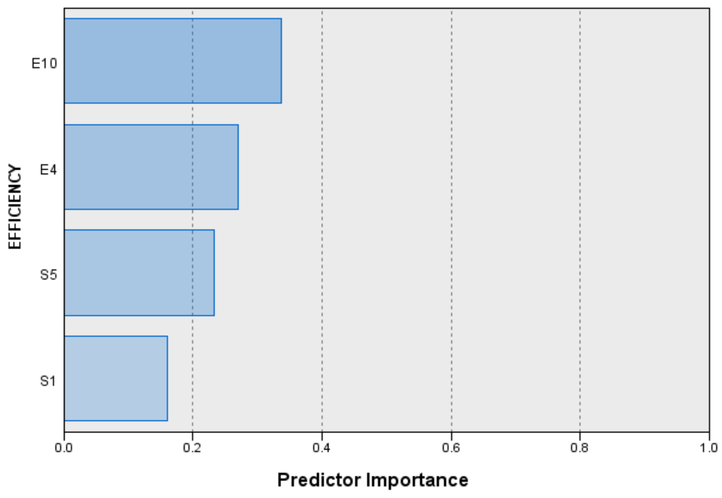


Figure 23 The most important variable affecting the crew efficiency factor

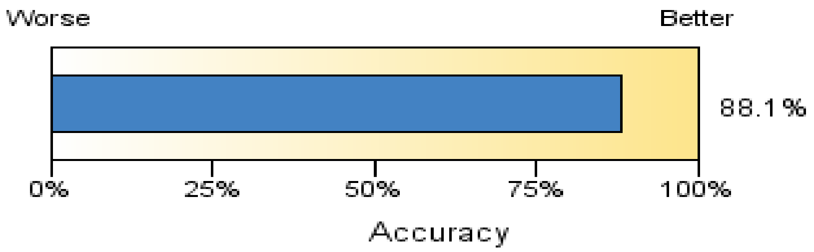


Figure 24 Prediction accuracy in evaluating crew efficiency variables

According to Figure 24, the modelling accuracy in predicting the variables that affect the crew efficiency factor is observed to be 88.1%.

4.4. Findings Part I

Figure 25 represents a subset of the available data, where a certain percentage is considered from each set. Consequently, during the processing stage, when a larger percentage of the available data is taken into account, it is expected that a larger portion of the data will be included in the proposed set. In the analysis and processing stages, termination conditions can be defined using a Gain diagram. Figure 25 is specifically related to testing the proposed model. Upon evaluating the model, it is evident that the gain chart for the inspector group has reached its peak at 100% with a slope of 10%.

For instance, the initial point on the curve corresponds to the inspector category (represented by the green line), and its coordinates are (100% and 10%). These coordinates indicate that if 10% of the cases from a data set are randomly selected, it can be expected that approximately 100% of all the cases in the inspector group will be included. The covered area and the 10% slope reflect the interest performance per inspector group.

The related chart representing various groups demonstrates successful performance in the arrangement process when they reach their peak in the upper range of the diagonal line, particularly at the lower percentages. The captain's group achieves a slope equal to 20%, the crew's group exhibits a slope of 30%, and the passengers' group reaches its peak with a slope of 40%. As the Gain graph for different groups lies in the upper range of the diagonal line and reaches a peak of 40%, it indicates a successful arrangement process.

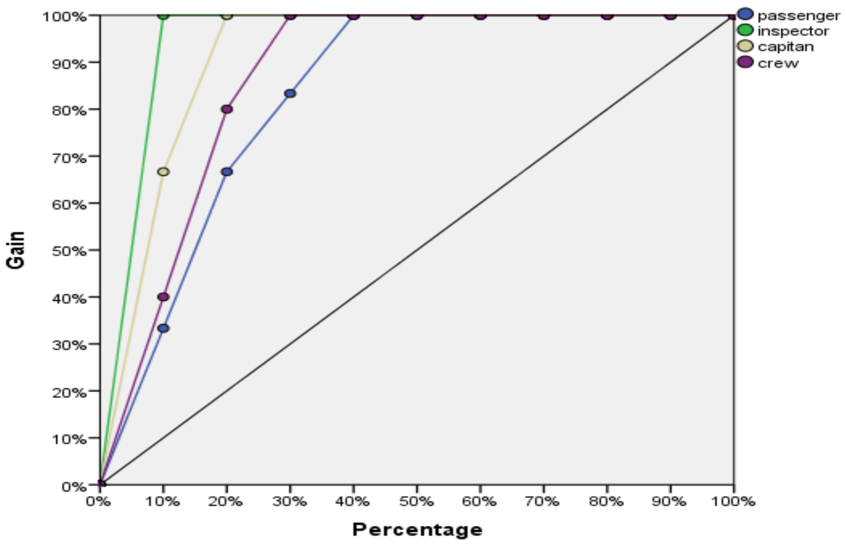


Figure 105 Gain chart for different groups

Figure 26 represents the gain diagram which is related to the stage of testing the proposed model concerning the variable "having previous experience of different groups in traveling by smart ship". By considering the covered area and the degree of slope (reaching the peak at a slope equal to 10%), it is evident that the gain diagram achieved greater success for passengers who had no prior experience of traveling with a smart ship.

Based on the statistics of passengers with previous experience of traveling on a smart ship, it is evident that the peak point of 100% has been achieved at a slope of 90%. Comparing the results for the factor of having experience in traveling with a smart ship reveals that passengers who travelled on a smart ship for the first time exhibited a similar behaviour pattern. This can be attributed to factors such as the safety and duration of the trip, the performance of the crew and captain, and the focus on environmental protection.

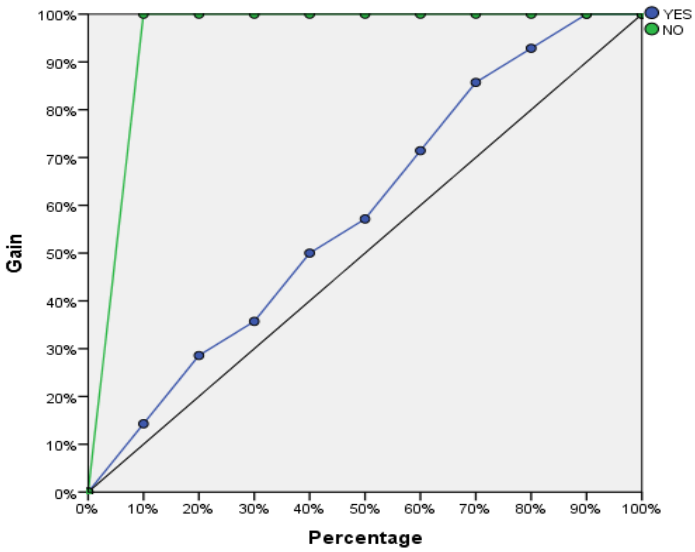


Figure 26 Gain chart for the factor of previous experience of different groups in traveling by intelligent ship

The lift diagram is a measure that indicates the increase in accuracy achieved by a proposed model compared to random selection. It evaluates the change process based on ranking and by checking all the points for each model, the best model is determined. According to diagram 27, which corresponds to the testing stage of the proposed model, it is evident that the model's performance was deemed acceptable for different groups. The area under the curve, situated between the baseline and the lift curve, is greater for the inspector group compared to the other groups, indicating the effectiveness of the model for this particular group.

The model's effectiveness for the captain group was given the next priority, followed by the crew and passenger groups, respectively, in terms of priority.

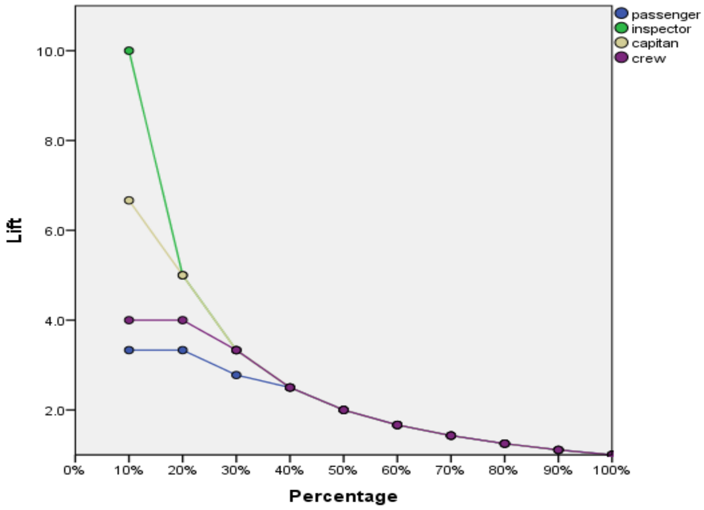


Figure 27 Lift chart for different groups

4.4.1. Independent variable importance

The examination of the importance of independent variables aims to determine the influence of changes in independent variable values (questions raised in relation to crew performance, passenger satisfaction, and energy sustainability) on the predicted values generated by the proposed network with a hidden layer. According to the obtained results, it is apparent that variable P5 holds the highest normalized significance equal to 100%, while variables S3 and S4 exhibit normalized significances of 95.8% and 95.1% respectively, indicating their greater importance. On the other hand, variables E10 and E5 are found to have the least normalized importance and are ranked lowest among the considered variables, respectively as illustrated in Figure 28.

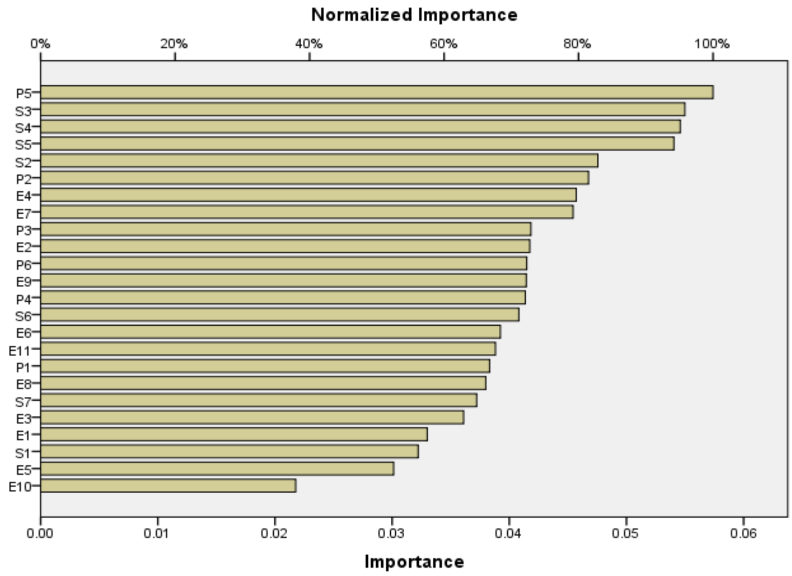


Figure 28 Independent variable importance

Figures 29 to 31 display the residuals of the proposed model for the three factors: passenger satisfaction, ship crew performance, and energy sustainability. These figures demonstrate that the remaining values for all three factors are very low, indicating the high accuracy of the predicted values by the proposed neural network. Additionally, the figures include the distribution curve (depicted by the black curve), which exhibits a strikingly similar pattern to the weighted residuals for the triple factors. The distribution curve serves as a criterion to evaluate changes in weighted residuals within the proposed neural network. It is expected that the pattern of changes in the weighted residuals should closely resemble the pattern observed in the distribution curve. This pattern typically involves an ascent, reaching the peak, and then a descent.

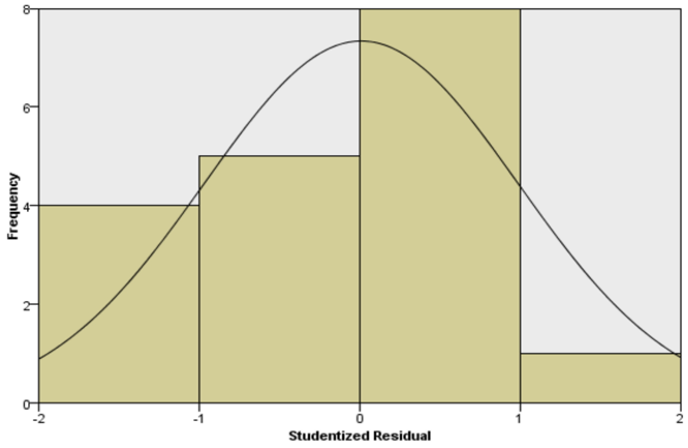


Figure 29 Weighted residual of passenger satisfaction by the proposed model

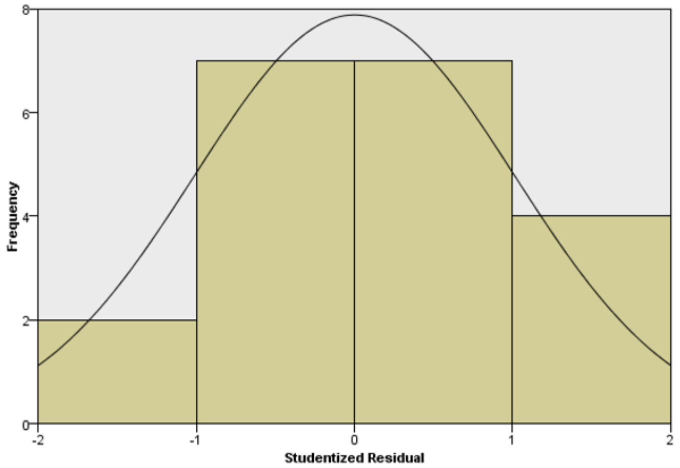


Figure 30 Weighted residual of crew performance by the proposed model

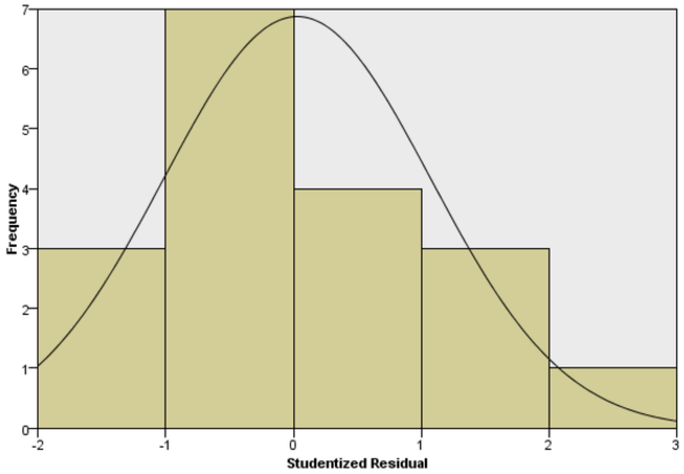


Figure 111 Weighted residue of energy stability by the proposed model

4.5. Discussion

Figure 32 displays the variables that have been selected for optimization, as indicated by the red arrows. The objective of this section is to perform the optimization process for the variables that were assigned the lowest priority based on the neural network's predictions. Therefore, the optimization process is specifically applied to variable S1, which is associated with the passenger satisfaction factor, variable E5, related to the crew performance factor, and variable E10, which pertains to energy sustainability and pollution factor. These variables were chosen with the aim to improve their performance and impact within the system.

The variables selected to perform the optimization process, have normalization importance percentage equal to 37.9, 52.5, and 56.1%, respectively. During the selection of variables for optimization, our main emphasis was on identifying the variables that had the least impact on each of the factors: pollution, passenger satisfaction, and crew performance.

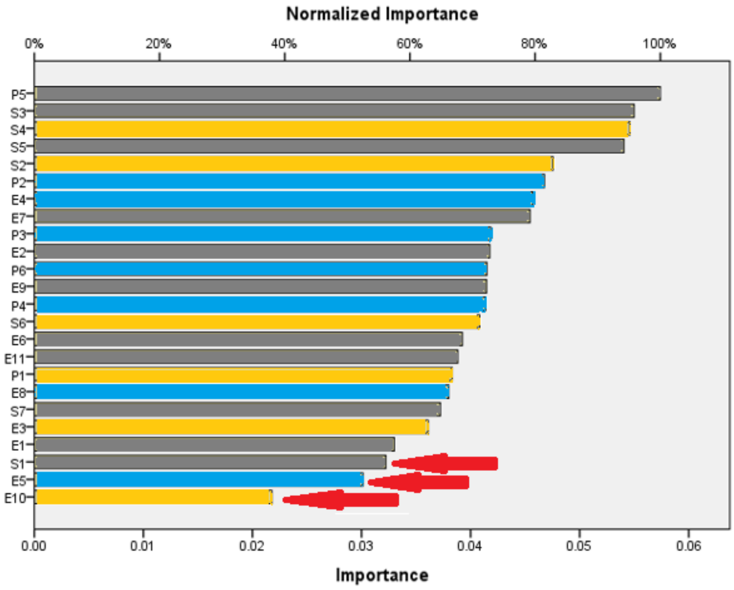


Figure 32 Selected variables in order to perform optimization

4.5.1 Evaluation of the correlation between the variables with the lowest priority

To carry out the optimization process, after determining the variables that had the lowest priority over the triple factors, it is now necessary to check their removal from the neural model. Figure 33 provides an overview of the process of assigning dependent and independent variables during the optimization stage. Initially, the variable "experience" was introduced as a dependent variable in the model, followed by defining the different groups who completed the questionnaire as dependent variables in the model.

Once the degree of correlation between the variables has been determined, several criteria mentioned in the subsequent sections of this research are employed to determine which of the three variables can be eliminated from the model. After determining the elimination of the variables with the lowest priority, the variables affecting the triple factors are prioritized by the neural network to check the optimization effect. This prioritization allows us to evaluate the effect of optimization on these variables and their impact on the overall system.

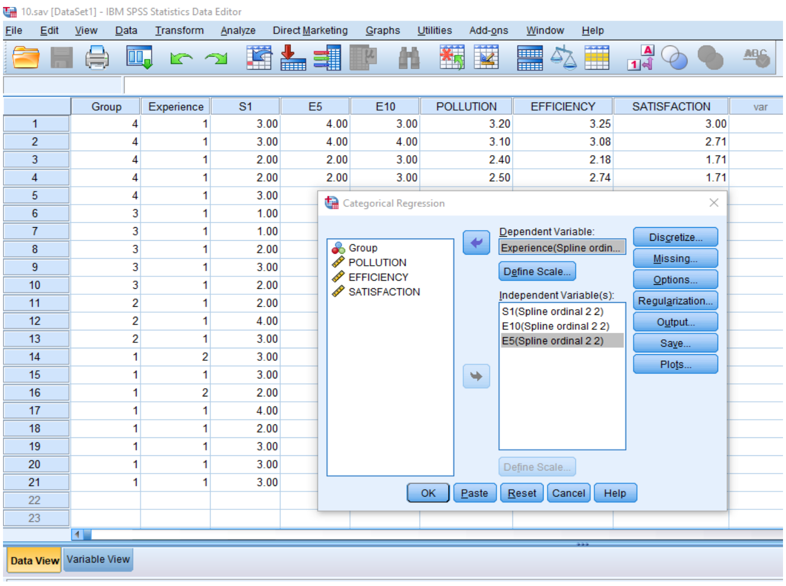


Figure 33 Definition of independent and dependent variables of the model

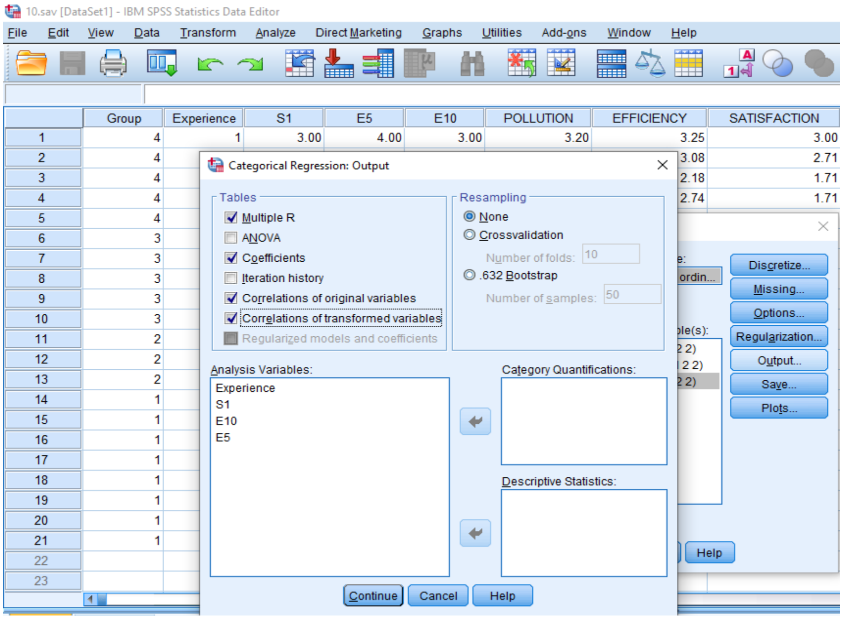


Figure 34 Selected variables (E10, E5 and S1) in order to optimize

Table 8 and 9 presents the correlation coefficients and eigenvalues of the predictor variables. As it can be seen in Table 4-4, the correlation coefficient of each variable with itself is equal to 1, indicating perfect correlation. For this reason, the main diameter of these tables all has a value of 1. Based on the following table, it is clear that there is no issue of collinearity between the predictor variables due to their low correlation values. Specifically, in Table 6, variables E10 and S1 exhibit the lowest correlation, while variables E5 and S1 show the highest correlation. Similar results were obtained in relation to the correlation values of variables related to pollution factors and crew performance, indicating consistency in the results.

Table 8 Correlation between the main variables and passengers' satisfaction

Variables	S1	E5	E10
S1	1.000	.448	.173
E5	.448	1.000	.419
E10	.173	.419	1.000
Dimension	1	2	3
Eigenvalue	1.706	.828	.467

Table 9 presents the correlation between transformed variables for passenger satisfaction and pollution. According to the tables, it is evident that variables E10 and E5 exhibit the lowest correlation, while variables E10 and S1 display the highest correlation with each other.

Table 9 Correlation between the transformed variables and passengers' satisfaction

Factor	Variables	S1	E5	E10
Passenger satisfaction	S1	1.000	.248	.344
	E5	.248	1.000	.175
	E10	.344	.175	1.000
	Dimension	1	2	3
Pollution	S1	1.000	.248	.344
	E5	.248	1.000	.175
	E10	.344	.175	1.000
	Dimension	1	2	3

In table 10, the coefficient of determination (R square) is presented, which serves as a criterion for evaluating the accuracy of the regression model. By analyzing the tables, it becomes apparent that the class regression model with the optimal scale accurately describes approximately 99% of the variation in the response variable. The dependent variables (passenger satisfaction, crew performance, and pollution) successfully generate predictive values (S1, E5, and E10) with an error rate of less than 0.05%.

The value of Adjusted R Square serves as a measure indicating the accuracy of the predicted values by the neural network. The table provided, demonstrate that the R square set achieved in the proposed neural network was approximately equal to 1.

Table 10 Evaluation of triple factor and predictors

Factor	R Square	Adjusted R Square	Apparent Prediction Error
satisfaction	.993	.989	.007
Crew efficiency	.953	.933	.047
pollution	.993	.989	.007

Table 11 presents the standardized coefficients in the regression model for each of the desired variables that had the least impact on the triple factors. The Categorical Regression model (CATREG) exclusively displays standardized coefficients, the reason for this is that each of the main variables of the system is first standardized and then applied to the regression model.

Based on the table below, it is evident that the beta value for variable E5 in relation to the passenger satisfaction factor is approximately 1 (beta equal to 1 indicates the full effectiveness of the variable). Additionally, the value of f, (which is a function of the correlation value of the variables), is smaller than 1 for the variable with lower-priority (variable E5, which holds higher priority compared to other variables). Upon observing the table and examining the Sig column, it becomes apparent that the variables S1 and E10 can be removed from the model.

Since the value of calculated Sig is greater than the evaluation error value, as a result, the hypothesis of low influence of this variable is confirmed. When evaluating the Sig value for the pollution and crew performance factors, it was observed that the calculated Sig value for two variables (S1 and E10) is greater than the evaluation error value.
Furthermore, the beta value for both the pollution and crew performance factors was less than 0.01. Based on these results, it can be concluded that the variables S1 and E10 can be removed from the proposed neural network.

Table 11 Dependent variable: Satisfaction

	Standardized Coefficients		d_f	F	Sig.
	Beta	Bootstrap (1000) Estimate of Std. Error			
S1	.035	.402	1	.007	.932
E5	.986	.468	4	4.433	.016
E10	.004	.226	1	.000	.987

All variables that have a Sig value greater than the evaluation error should not be removed from the model at the same time. The process of removing low-impact variables should be done separately so that the model is presented based on the most important variables and the optimal number. To identify the importance of each of the predictor variables and their relationship with the response variable, it is reasonable to refer to the zero-order correlation coefficient, partial correlation coefficient and partial correlation coefficient.

It is important to note that all variables with a Sig value greater than the evaluation error should not be removed from the model simultaneously. The process of eliminating low-impact variables should be conducted separately so that the model is presented based on the most important variables and the optimal number. To identify the importance of each predictor variable and their relationship with the response variable, it is reasonable to consider the zero-order correlation coefficient, partial correlation coefficient, and partial correlation coefficient.

In table 12, the importance of the variables based on the correlation for the passenger satisfaction factor is presented. The importance of variables is directly related to their correlation values, and correlation can be considered as a criterion for determining low impact variables. As can be seen in the importance column of the table below, variable E5 has the greatest impact on the response variables (passenger satisfaction). The higher the correlation value, the greater the significance of the variable in relation to the response variable.

Variable E10 is considered the least influential and is given the lowest priority among the variables. By examining other factors such as crew performance and pollution, it was observed that variable E5 had the highest correlation in terms of zero, partial, and partial correlation. Variable E5 exhibited a correlation value almost equal to 1, indicating a strong relationship with the factors. Conversely, variable E10 showed the lowest correlation across all three factors, indicating its low importance in the model.

Table 12 Evaluating the importance of predictor variables for the satisfaction factor

Factor	Correlations			Importance
	Zero-Order	Partial	Part. Co.	
S1	.281	.347	.032	.010
E5	.996	.996	.951	.989
E10	.189	.039	.003	.001

Drawing the desired variables with the aim of optimizing the model against their scaled changes can have a significant impact on the optimization process and correct understanding of the model. These graphs, which are also known as transformation graphs, can have different slopes based on the type of defining variable.

In Figures 35 and 37, which belong to variables S1 and E10, respectively. These graphs show that, as a result of the conversion process in the target variables, the quantity of variables has taken an upward trend.

This upward trend indicates that these variables can be removed from the model. However, in Figure 36, it can be seen that as a result of the conversion of target variables, the quantity of variables has an almost horizontal slope, which is the reason for not removing this variable from the model.

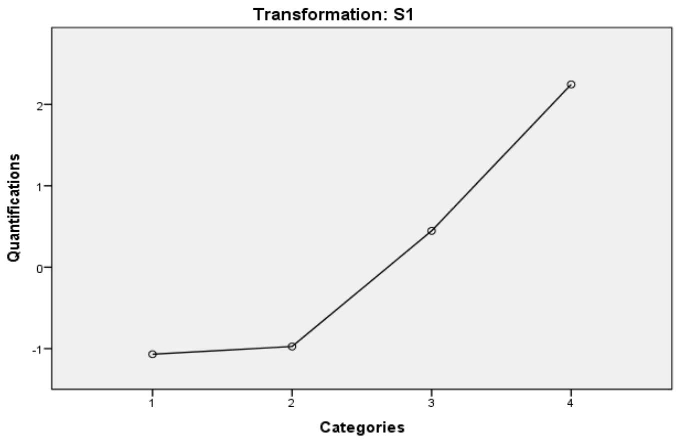


Figure 35 Diagram of transformation process per variable S1

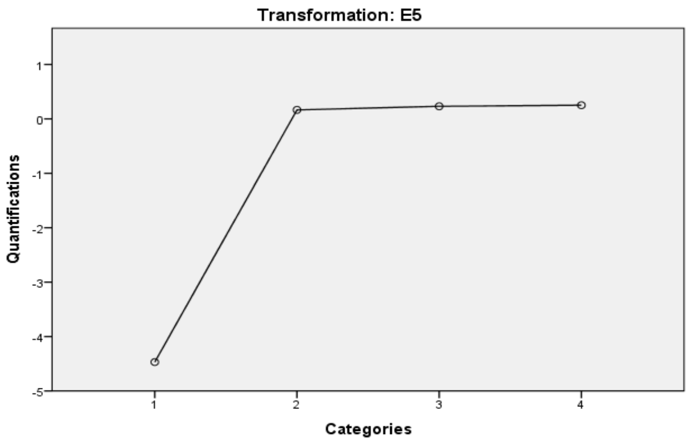


Figure 36 Diagram of transformation process per variable E5

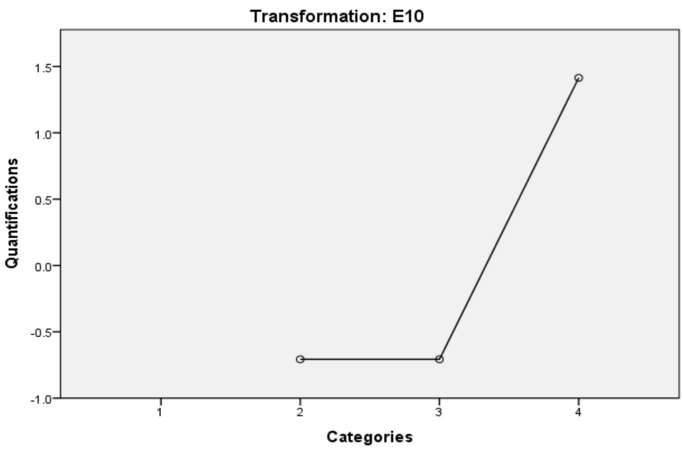


Figure 37 Diagram of transformation process per variable E10

4.5.2. Evaluation of results based on optimization

In this part, the results of the optimization process performed on low-impact variables based on three factors: passenger satisfaction, crew performance, and fuel stability are discussed. After considering the input from the crew, passengers, captain, and inspector, the two variables with the least impact were identified and removed. Subsequently, the remaining variables were re-analyzed using the neural network. The probabilistic function predicted by the proposed neural network for different groups is analyzed in this section after the optimization process. For this purpose, the training of the proposed neural network was conducted based on the optimization results and the elimination of low-impact variables from the system. The frequency of data in each category was then predicted. For the predictions obtained from the neural network, all error values and accuracy of the model were evaluated, and the average prediction error in the test and training stages for two variables of experience and different groups was equal to 0 and 9.4%.

Table 13 presents the partial and overall forecast percentages for different groups (crew, passengers, captain, and inspector) across different layers.

Table 13 Predicted results for different groups

Sample	Observed	Predicted				
		Passenger	Inspector	Captain	Crew	Percent Correct
Training	Passenger	7	0	0	0	100.0%
	Inspector	0	1	0	0	100.0%
	Captain	0	0	4	1	80.0%
	Crew	0	0	0	3	100.0%
	Overall Percent	43.8%	6.3%	25.0 %	25.0 %	93.8%
Testing	Passenger	0	0	0	0	0.0%
	Inspector	0	1	0	0	100.0%
	Captain	0	0	0	0	0.0%
	Crew	0	0	0	2	100.0%
	Overall Percent	0.0%	33.3%	0.0%	66.7 %	100.0%

According to table 4-9, the prediction accuracy percentages for the passenger group in both training and test layers for 7 prediction samples is equal to 100%. Similarly, the prediction accuracy percentage for the captain group in the training phase is 100% for 4 prediction samples. For the ship crew group, the prediction accuracy percentages in the training and testing layers are both 100% for 4 and 2 prediction samples, respectively.

The probabilistic function predicted by the proposed network after performing the optimization process for the experience criterion is investigated in this section. According to the optimization results and the removal of variables E10 and S1, the input and output variables for the proposed neural network were considered.

According to Table 14, the partial and overall forecast percentages for different layers are presented. In the training layer, the percentage of prediction accuracy for the variable "having previous experience in traveling with a smart ship (yes)" is equal to 87.5% for 14 prediction samples. Additionally, in the test layer, the percentage of prediction accuracy for "having no previous experience in traveling with a smart ship (no)" was equal to 100% for 3 prediction samples.

Table 14 Predicted results for the experience criterion

Sample	Observed	Predicted		
		Yes	No	Percent Correct
Training	Yes	14	0	100.0%
	No	2	0	0.0%
	Overall Percent	100.0 %	0.0%	87.5%
Testing	Yes	3	0	100.0%
	No	0	0	0.0%
	Overall Percent	100.0 %	0.0%	100.0%

After applying the optimization process, the overall percentage of correct prediction for the testing and training parts was obtained as 100% and 90.6% respectively. These results demonstrate the high accuracy of the proposed neural network in predicting the variables.

Figure 38 represents the testing of the proposed model. The evaluation of the model reveals that the interest graph for the inspector group reaches a peak of 100% at a slope of 10%. Similarly, the crew group reaches its peak at a 30% slope, while the captain's group and the passenger group reach their peak at a 40% slope. The gain diagram of different groups aligns with the upper range of the diagonal line, and they have reached their peak in the mentioned percentages. These observations indicate a successful arrangement process.

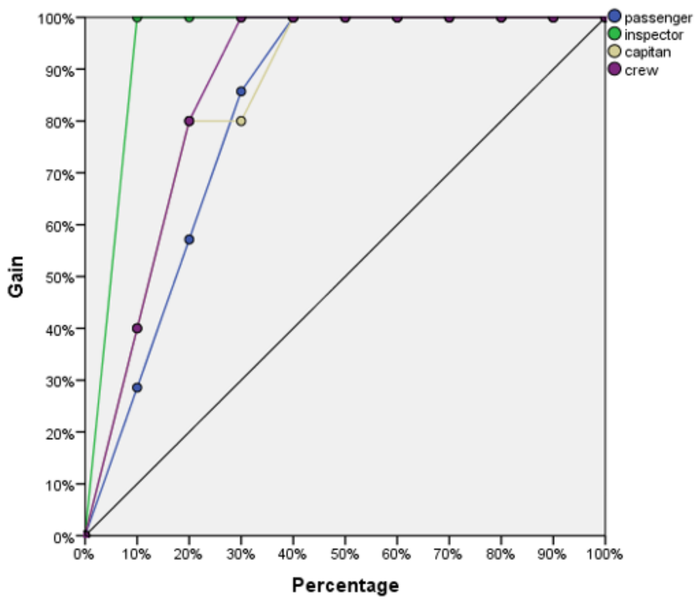


Figure 38 Profit graph for different groups after optimization

Figure 39 represents the gain diagram for the test phase of the proposed model regarding the variable "having previous experience of different groups in traveling by smart ship." The gain plot demonstrates successful performance based on the surface covered and the degree of slope, particularly peaking at a slope equal to 10% for the "Yes" variable. For passengers with no previous smart ship travel experience, the gain curve reaches its peak at a slope of 20%, while for passengers with previous smart ship travel experience, it peaked at a slope of 90%.

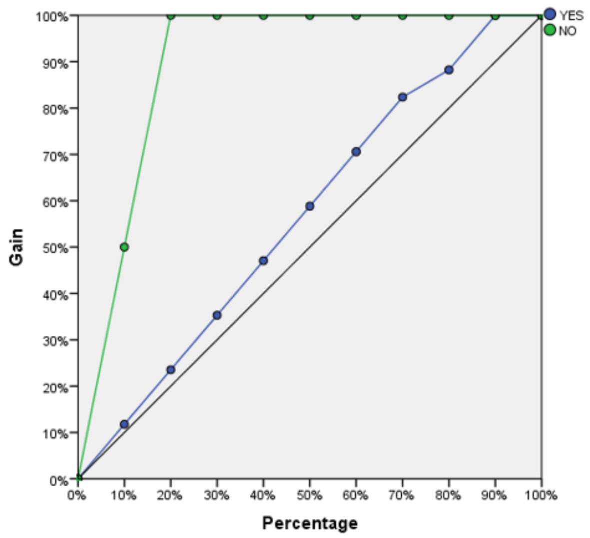


Figure 39 Profit diagram after the optimization process for the previous experience factor of different groups in traveling by smart ship

According to diagram 4-9, which is related to the testing stage of the proposed model and based on the performance of the model, it is clear that the performance of the model was acceptable for different groups. The area under the curve that is placed between the base line and the lift curve for the inspector group is more compared to the rest of the groups, indicating the effectiveness of the model for this group. Following that, the effectiveness of the model for the crew group was given the next priority. The effectiveness of the model for the captain and passenger groups were ranked as the next priorities, respectively.

After optimization, the lift diagram reveals a decrease in the area under the curve between the base line and the lift curve for both the captain and passenger groups. This decrease can be attributed to the direct relationship between the lift chart and the gain chart. The removal of two variables E10 and S1 results in a smaller percentage of the available data being considered. Consequently, it is expected that a smaller percentage of the data will be included in the proposed collection.

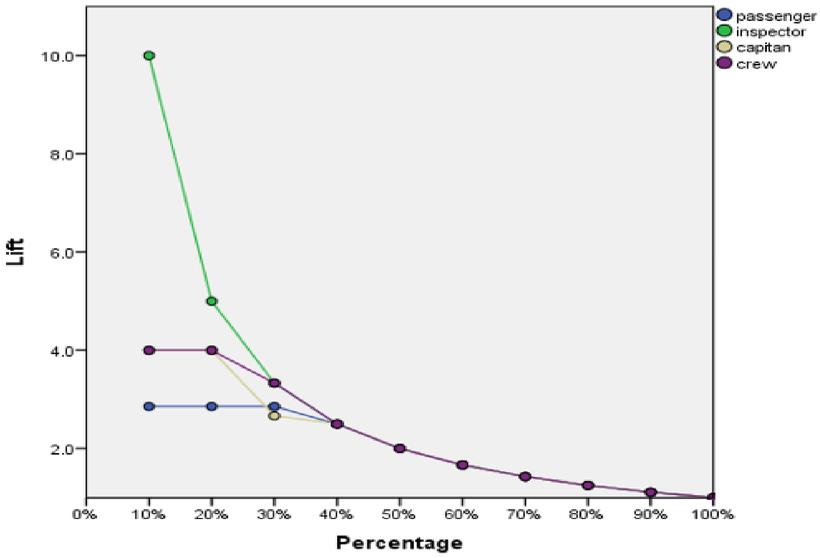


Figure 40 Lift diagram after the optimization process for different groups

The table below presents a comparison of the importance and normalized importance of the variables before and after the optimization process. After performing the optimization process for the variables with the lowest priority among the three factors, it was observed that the E7 and P5 variables gained the highest priority. The optimization process resulted in an increase in the average importance percentage of the variables, highlighting the significance of the optimization process in the proposed system.

Table 15 Comparison of the results according to the importance percentage of model variables

After optimization			Before optimization		
Variable	*Importance*	*Normalized Importance*	*Variable*	*Importance*	*Normalized Importance*
E1	*.049*	*79.3%*	*E1*	*.033*	*57.5%*
E2	*.044*	*71.0%*	*E2*	*.042*	*72.7%*
E3	*.044*	*71.7%*	*P1*	*.038*	*66.8%*
S2	*.042*	*67.7%*	*S3*	*.055*	*95.8%*
P2	*.053*	*86.6%*	*E4*	*.046*	*79.7%*
S3	*.049*	*79.3%*	*P3*	*.042*	*72.9%*
E4	*.032*	*52.5%*	*S4*	*.055*	*95.1%*
P3	*.049*	*80.3%*	*P4*	*.041*	*72.1%*
S4	*.038*	*61.9%*	*E7*	*.045*	*79.2%*
S5	*.032*	*52.7%*	*P5*	*.057*	*100.0%*
E6	*.033*	*54.3%*	*S6*	*.041*	*71.1%*
P4	*.051*	*83.2%*	*E8*	*.038*	*66.2%*
P5	*.054*	*87.9%*	*P6*	*.041*	*72.3%*
S6	*.049*	*78.9%*	*E9*	*.041*	*72.2%*
E8	*.050*	*81.7%*	*E3*	*.036*	*62.9%*
P1	*.043*	*70.3%*	*S1*	*.032*	*56.1%*
E5	*.040*	*65.7%*	*S2*	*.048*	*82.9%*
E7	*.062*	*100.0%*	*E5*	*.030*	*52.5%*
P6	*.043*	*70.1%*	*S5*	*.054*	*94.2%*
E9	*.042*	*68.1%*	*E10*	*.022*	*37.9%*
S7	*.050*	*81.5%*	*S7*	*.037*	*64.8%*
E11	*.048*	*78.3%*	*E11*	*.039*	*67.6%*
-	-	-	*P2*	*.047*	*81.5%*
-	-	-	*E6*	*.039*	*68.4%*

According to the obtained results, variable E7 demonstrates with the highest normalized significance equal 100%, while variables P5 and P2 exhibit normalized significance values equal to 87.9% and 86.6% respectively, indicating their importance. On the other hand, variables S5 and E4 have the least normalized importance among the variables.

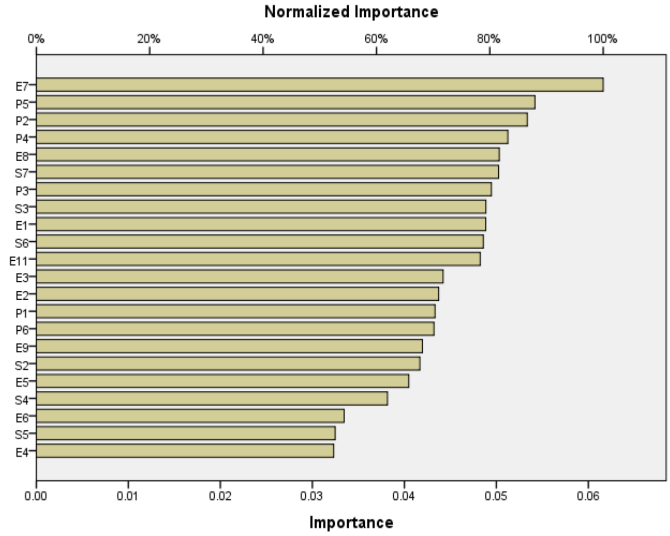


Figure 41 Independent variable importance after the optimization process

In this chapter, the impact of smart network on the marine fleet during short-term trips was investigated using a neural network. Data collection was done in the field and based on the prepared questionnaire. Completion of this questionnaire was done based on the opinions of different groups including passengers, crew, ship captain and ship inspector. After completing the questionnaire, the definition of the neural network and the components of the training and testing processes were discussed. In the process of testing and training the system, the aim was to increase the accuracy of the model as much as possible by prioritizing the variables without the least error.

Based on the results of the proposed neural network, it was found that before the optimization process, variable P5 held the highest priority among different groups, including passengers, crew, captain and inspector.

According to the neural network analysis, variables E10, S1, and E5 were identified as having the least importance, while the importance of other variables was enhanced through the optimization process. This optimization process was performed using the regression model, which resulted in the exclusion of the two variables, E10 and S1 from the priority of the desired variables, while the remaining variables were reassessed and prioritized again.

After conducting the optimization, training, and testing of the evaluation system, it was observed that the average importance percentage of the variables had increased. As a result of the optimization process, variable E7 emerged as the highest priority among different groups, including passengers, crew, captain, and inspector. On the other hand, variables S5 and E4 were ranked at the lowest level of prioritization among the effective variables. Based on the findings of this research, the implementation of a smart network in the marine fleet can have a significant impact on fulfilling the three factors, as perceived by the aforementioned groups.

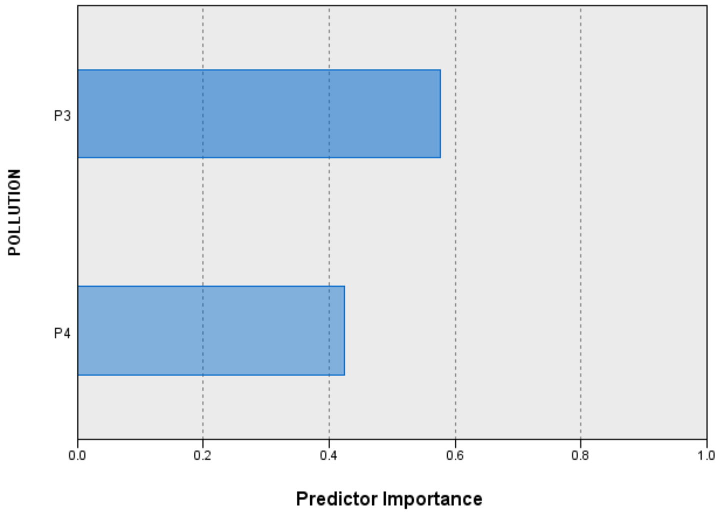


Figure 122 The most important variable affecting the pollution factor

According to Figure 42, it can be seen that among the variables affecting pollution, variable P3 has the most predicting importance. The topic of this variable was related to not wasting passengers' time in the process of boarding the ship.

Variable P3 was related to:

"Is the intelligent system effective in preventing time wasted when passengers board the ship?"

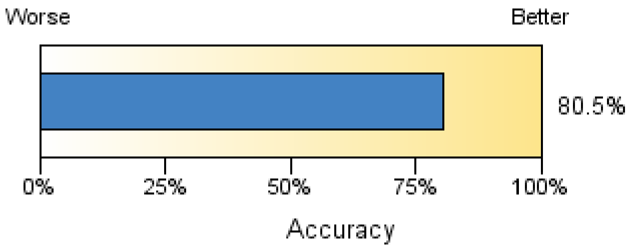


Figure 43 Prediction accuracy in evaluating pollution factor

According to the prediction results of the neural network (Figure 43), it can be seen that the modelling accuracy is equal to 80.5%, which indicates the high accuracy of the proposed network. In Figure 44, the results obtained for the most effective variables on the passenger satisfaction factor are presented.

According to the prediction results of the neural network presented in Figure 44, it can be seen that among the variables affecting the passenger satisfaction factor, the S4 variable is the most important. This variable was related to predicting the shortest route and reducing the length of travel.

Variable S4 was:

"Does the intelligent system have an effect in predicting the shortest sea route (in order to reduce fuel consumption and travel time)? "

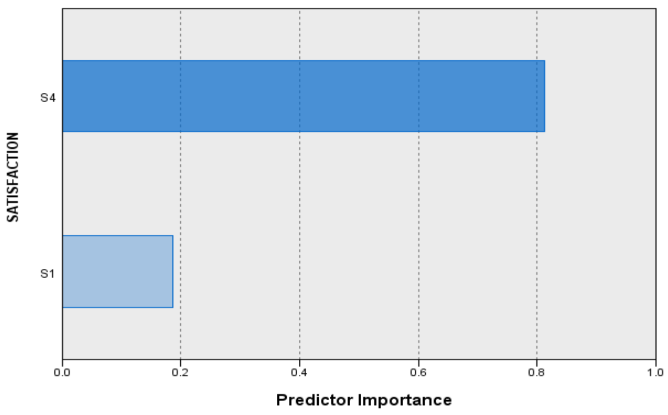


Figure 44 The most important variable affecting the passenger satisfaction factor

According to Figure 45, it can be seen that the accuracy of modeling in predicting variables affecting passenger satisfaction factor is 85.4%.

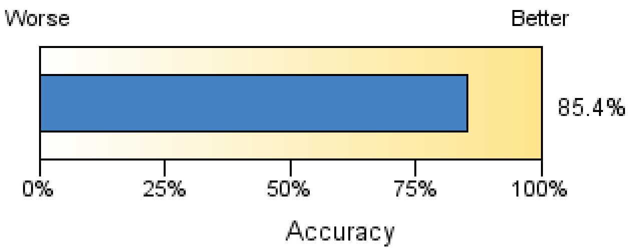


Figure 413 Prediction accuracy in evaluating satisfaction factor

In Figure 46, the results obtained for the most effective variable on the ship crew performance factor are presented.

According to the prediction results of the neural network presented in Figure 46, it can be seen that among the variables affecting the crew's performance factor, the E10 variable is the most important. This variable was related to reducing fuel consumption and not wasting travel time.

The variable E10 was in relation with:

"Is the launch of the intelligent ship system beneficial for the marine fleet in the long run by reducing the cost of fuel consumption and not wasting travel time?"

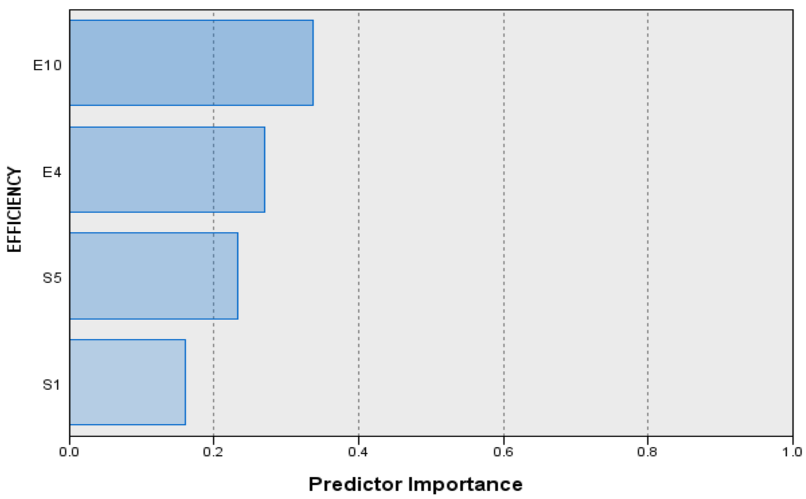


Figure 46 The most important variable affecting the crew efficiency factor

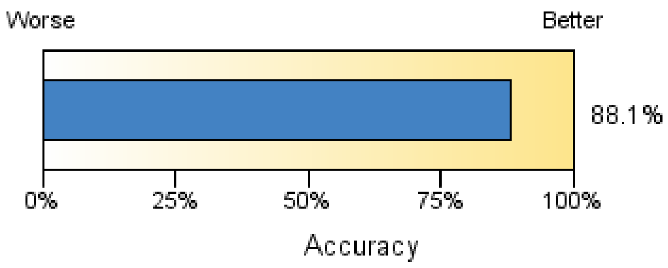


Figure 47 Prediction accuracy in evaluating crew efficiency variables

According to Figure 47, it can be seen that the accuracy of modeling in predicting variables affecting crew efficiency factor is 88.1%.

4.6. Findings Part II

Figure 48 covers a certain percentage of the data in each set for a certain percentage of the total available data. Therefore, in the processing stage, taking into account a larger percentage of the available data, it should be expected that a larger percentage of the data will be included in the proposed set. A Gain diagram can be used to define termination conditions in the analysis and processing stages. Figure 48 is related to testing the proposed model. Based on the evaluation of the model, it can be seen that the gain chart for the inspector group has reached the peak of 100% at a slope of 10%.

For example, the first point on the curve belongs to the inspector category (green line), which has coordinates as (100% and 10%). These coordinates show that if 10% of the cases in a data set are randomly selected, it should be expected that it will include about 100% of all the cases that are included in the inspector group. The area covered and the slope of 10% show the interest performance per inspector group.

The chart related to different groups, if they reach their peak in the upper range of the diagonal line and in the lower percentages, it indicates a successful performance in the arrangement process. The captain's group is at a slope equal to 20%, the crew's group is at a slope equal to 30%, and the group of passengers has reached its peak with a slope of 40%. Since the graph of the Gain of different groups is in the upper range of the diagonal line and has peaked at 40%, it indicates a successful arrangement process.

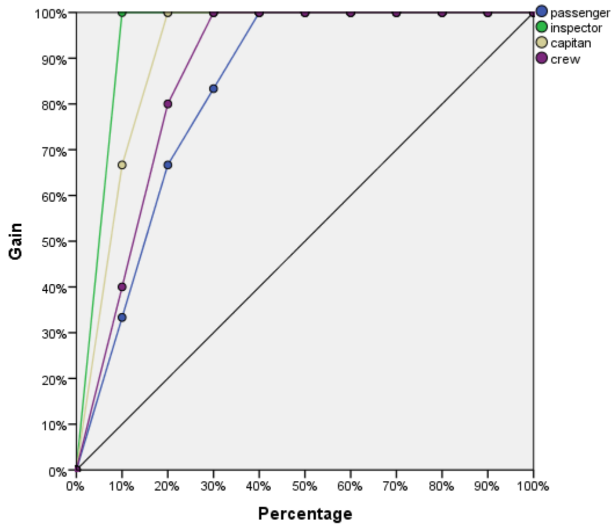


Figure 48 Gain chart for different groups

Figure 49 is the gain diagram related to the stage of testing the proposed model for the variable "having previous experience of different groups in traveling by smart ship". Considering the area covered and the degree of slope (reaching the peak at a slope equal to 10%), it can be seen that the gain diagram was more successful for passengers who had no previous experience of traveling with a smart ship.

According to the statistics of passengers who have had the previous experience of traveling with a smart ship, it can be seen that the peak point of 100% has been reached at a slope of 90%. Comparing the results for the factor of having experience in traveling with a smart ship shows that the passengers who travelled with a smart ship for the first time had a similar behaviour pattern due to the safety and duration of the trip, the performance of the crew and captain, and the protection of the environment.

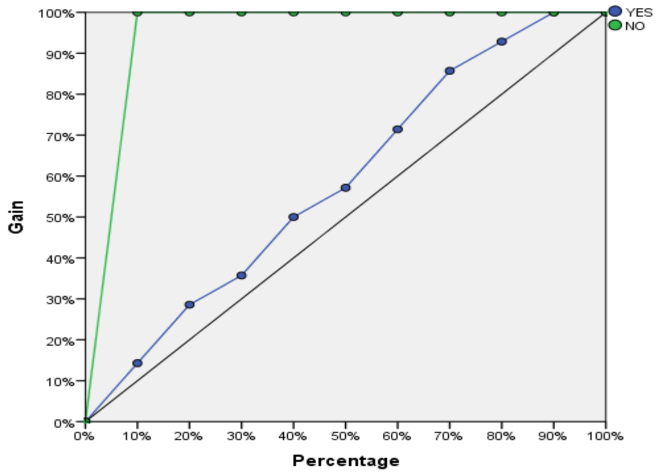


Figure 49 Gain chart for the factor of previous experience of different groups in traveling by intelligent ship

The lift diagram is a measure that shows the increase in accuracy in a proposed model compared to random selection and evaluates the change process according to the ranking, and by checking all the points for each model, the best model is determined. According to diagram 4-9, which is related to the testing stage of the proposed model and based on the performance of the model, it is clear that the performance of the model was acceptable for different groups.

The area under the curve that is placed between the base line and the lift curve for the inspector group is more than the rest of the groups, which indicates the effectiveness of the model for this group. Also, the effectiveness of the model for the captain group was given the next priority. The effectiveness of the model for crew and passenger groups were placed in the next priorities respectively.

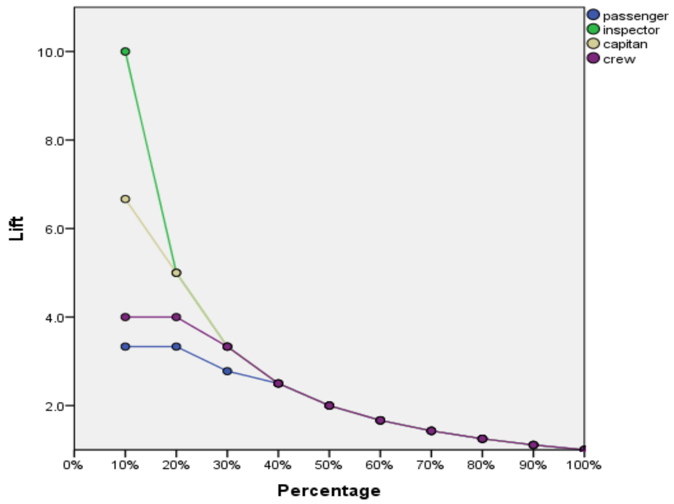


Figure 50 Lift chart for different groups

4.6.1. Independent variable importance

Examining the importance of independent variables is done in order to determine the impact of changes in independent variable values (questions raised in relation to crew performance and passenger satisfaction and energy sustainability) on predicted values (proposed network with a hidden layer). According to the obtained results, it can be seen that the variable p5 with normalized significance equal to 100% and the variables S3 and s4 with normalized significance equal to 95.8% and 95.1% respectively have more importance. Also, variables E10 and E5 had the least normalized importance, respectively.

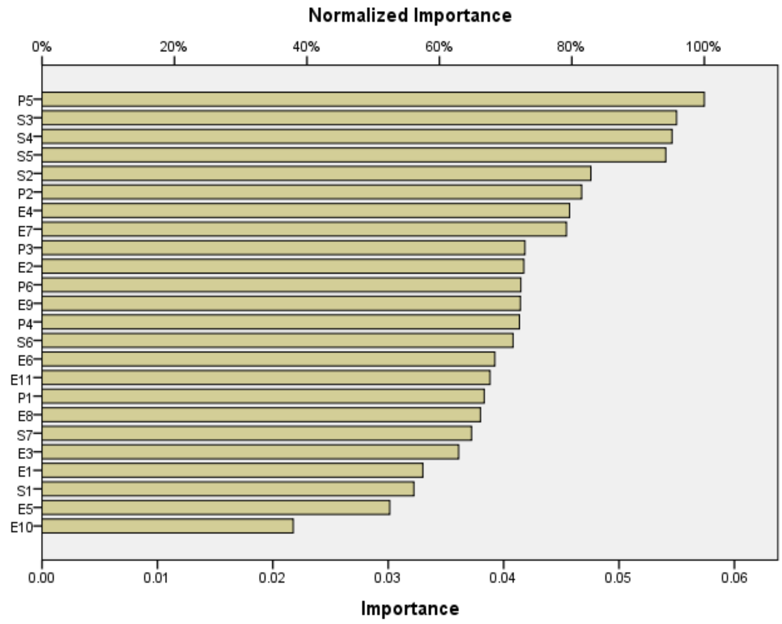


Figure 51 Independent variable importance

The figures 52 to 54, the residuals of the proposed model are presented for the three factors of passenger satisfaction, ship crew performance, and energy sustainability. According to the above figures, it can be seen that the remaining values for three factors are very low, which indicates the high accuracy of the values predicted by the proposed neural network. In these figures, the distribution curve (black curve) is also presented, and it can be seen that the distribution curve and the weighted residuals for the triple factors have an almost similar pattern. The distribution curve in order to evaluate the changes of weight residuals in the proposed neural network can be a criterion that the pattern of changes should be almost similar to the pattern of the distribution curve (a pattern including ascent and reaching the peak and descent).

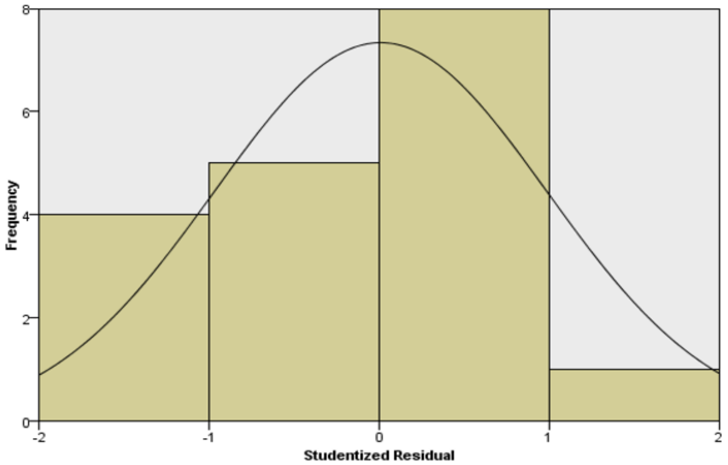


Figure 52 Weighted residual of passenger satisfaction by the proposed model

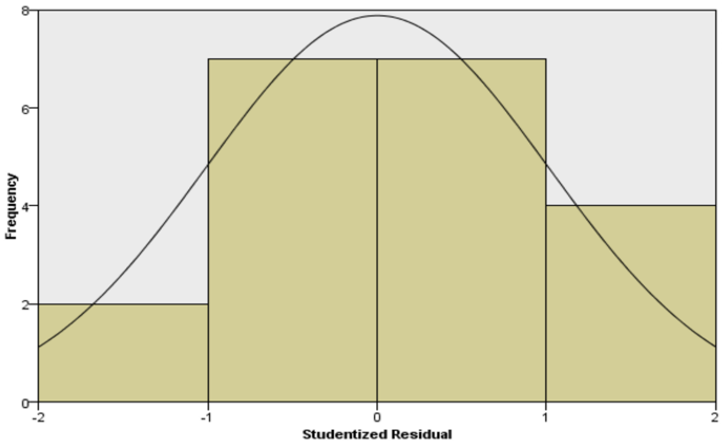


Figure 53 Weighted residual of crew performance by the proposed model

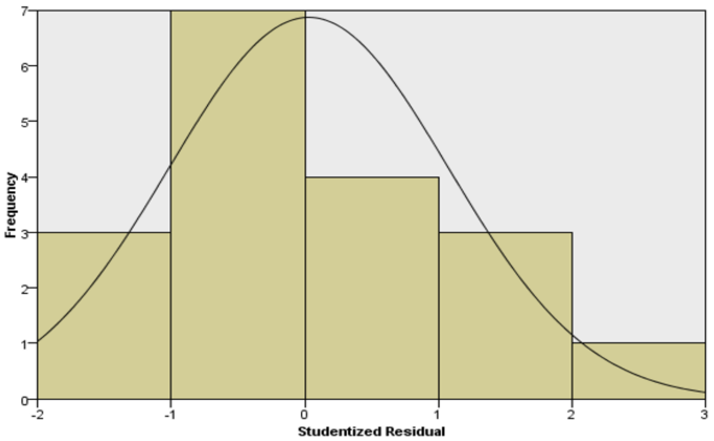


Figure 54 Weighted residue of energy stability by the proposed model

4.7. Discussion

In Figure 55, the variables that were selected for optimization (these variables are marked with red arrows) are presented. In this section, the goal is to perform the optimization process for the variables that had the lowest priority based on the prediction of the neural network. Therefore, variable S1 related to passenger satisfaction factor and variable E5 related to crew performance factor and variable E10 related to energy sustainability and pollution factor were selected and the optimization process is applied to these variables.

The variables selected to perform the optimization process, their normalization importance percentage is equal to 37.9, 52.5 and 56.1% respectively. In the selection of variables for the purpose of optimization, we tried to select the variables that had the least impact on each of the factors of pollution, passenger satisfaction and crew performance.

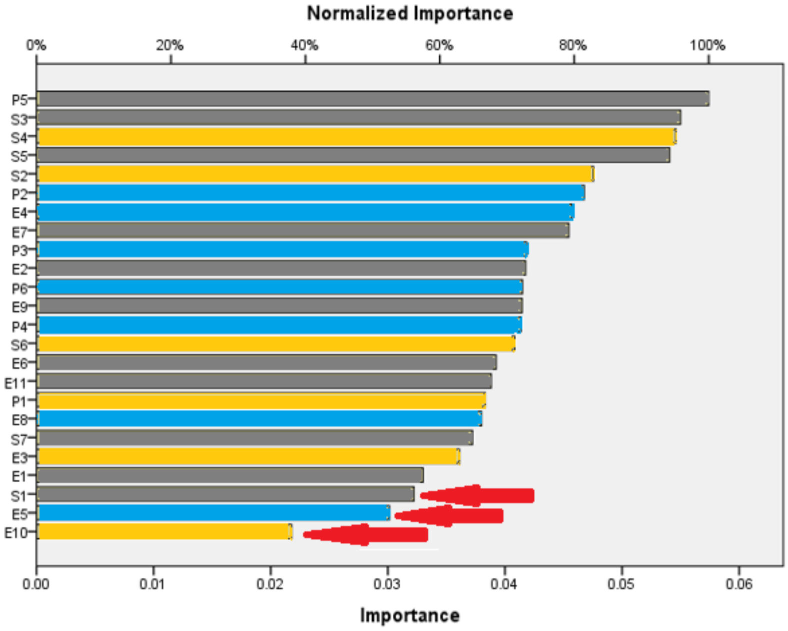


Figure 55 Selected variables in order to perform optimization

4.7.1 Evaluation of the correlation between the variables with the lowest priority

To carry out the optimization process, after determining the variables that had the lowest priority over the triple factors, it is now necessary to check their removal from the neural model. Figure 56 shows the process of assigning dependent and independent variables during optimization. At first, experience was introduced as a variable dependent on the model, and then different groups who completed the questionnaire were defined as variables dependent on the model.

After determining the degree of correlation between the variables, various criteria mentioned in the next sections of this research are used to determine which of these three variables can be removed from the model. After determining the elimination of the variables that had the lowest priority, the variables affecting the triple factors are prioritized by the neural network to check the optimization effect.

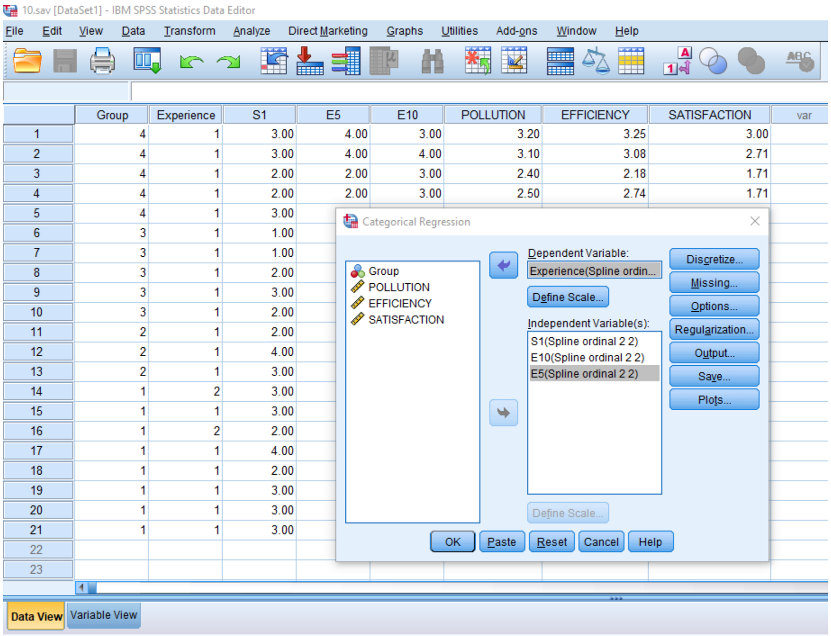


Figure 514 Definition of independent and dependent variables of the model

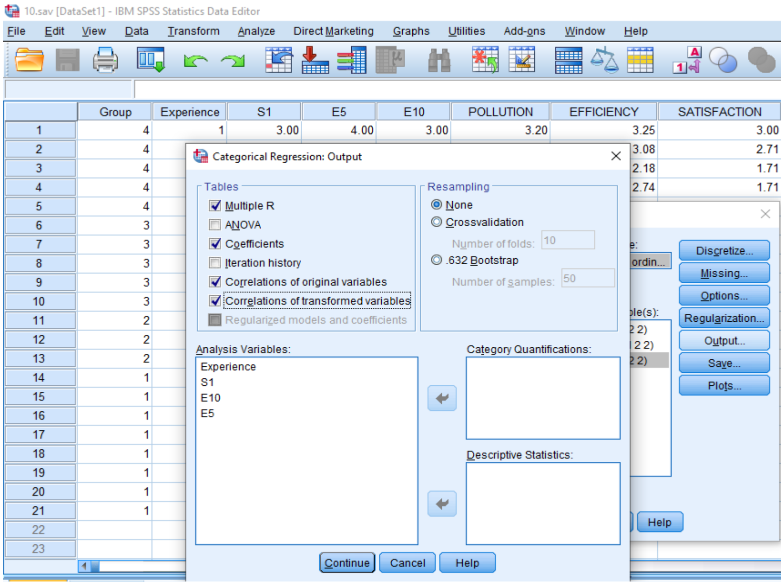


Figure 515 Selected variables (E10, E5 and S1) in order to optimize

Table 16 shows the correlation coefficients between predictor variables along with their eigenvalues. As can be seen in Table 16, the correlation coefficient of each variable with itself is equal to 1. For this reason, the main diameter of these tables all have a value of 1. Based on the following table, it is clear that there is no problem of collinearity between the predictor variables (due to the low correlation value). According to Table 16, variables E10 and E1 have the lowest correlation and variables E5 and S1 have the highest correlation. For pollution factors and crew performance, similar results were obtained regarding the correlation value of the variables.

Table 16 Correlation between the main variables and passengers' satisfaction

Variables	S1	E5	E10
S1	1.000	.448	.173
E5	.448	1.000	.419
E10	.173	.419	1.000
Dimension	1	2	3
Eigenvalue	1.706	.828	.467

Table 17 show the correlation between transformed variables for passenger satisfaction and pollution. According to the table, it can be seen that variables E10 and E5 have the lowest correlation and variables E10 and S1 have the highest correlation with each other.

Table 17 Correlation between the transformed variables and passengers' satisfaction

Factor	Variables	S1	E5	E10
Passenger satisfaction	S1	1.000	.248	.344
	E5	.248	1.000	.175
	E10	.344	.175	1.000
	Dimension	1	2	3
Pollution	S1	1.000	.248	.344
	E5	.248	1.000	.175
	E10	.344	.175	1.000
	Dimension	1	2	3

In tables 18, the coefficient of determination (R square) is presented, which is a criterion for evaluating the accuracy of the regression model. According to the following table, it can be seen that almost 99% of the variation of the response variable is described by the class regression model with the optimal scale. The dependent variables (passenger satisfaction and crew performance and pollution) were able to provide predictive values (S1, E5 and E10) with an error of less than 0.05%.

The value of Adjusted R Square is a measure that shows the accuracy of the values predicted by the neural network. According to the following table, it can be seen that the R square set in the proposed neural network was approximately equal to 1.

Table 18 Evaluation of triple factor and predictors

Factor	**R Square**	**Adjusted R Square**	**Apparent Prediction Error**
satisfaction	.993	.989	.007
Crew efficiency	.953	.933	.047
pollution	.993	.989	.007

Table 19 includes the standard coefficients in the regression model for each of the desired variables, which had the least impact on the triple factors. Category regression model contains only standardized coefficients, the reason for this is that each of the main variables of the system is first standardized and then applied to the regression model.

According to the table below, it can be seen that the beta value for variable E5 for the passenger satisfaction factor is approximately equal to 1 (beta equal to 1 indicates the full effectiveness of the variable). Also, the value of f (which is a function of the correlation value of the variables) is smaller than 1 for the low-priority variable (variable E5 has a higher priority than the other variables). According to the table below and based on the Sig column, it is clear that the variables (S1 and E10) can be removed from the model.

Since the value of calculated Sig is greater than the value of the evaluation error, as a result, the hypothesis of low influence of this variable is confirmed. By evaluating the value of Sig for two factors (pollution and crew performance), it was observed that the value of Sig calculated for two variables (S1 and E10) is greater than the value of the evaluation error. Also, the beta value for two factors (pollution and crew performance) was less than 0.01. These results confirm that the variables S1 and E10 can be removed from the proposed neural network.

Table 19 Dependent variable: Satisfaction

	Standardized Coefficients		d_f	F	Sig.
	Beta	Bootstrap (1000) Estimate of Std. Error			
S1	.035	.402	1	.007	.932
E5	.986	.468	4	4.433	.016
E10	.004	.226	1	.000	.987

All variables that have a Sig value greater than the evaluation error should not be removed from the model at the same time. The process of removing low-impact variables should be done separately so that the model is presented based on the most important variables and the optimal number. To identify the importance of each of the predictor variables and their relationship with the response variable, it is reasonable to refer to the zero-order correlation coefficient, partial correlation coefficient and partial correlation coefficient.

In table 20, the importance of the variables based on the correlation for the passenger satisfaction factor is presented. The importance of variables has a direct relationship with their correlation value, and correlation can be considered as a criterion for determining low impact variables. As can be seen in the importance column of the table below, variable E5 has the greatest impact on the response variables (passenger satisfaction).

As the least influential variable, E10 is prioritized last. By examining other factors (crew performance and pollution), it was observed that the correlation of the variables (zero and partial and partial correlation) is the highest for factor e 5 (correlation value of variable e 5 was almost equal to 1). Also, for triple factors, variable e 10 had the lowest correlation, which indicates the low importance of this variable.

Table 20 Evaluating the importance of predictor variables for the satisfaction factor

Factor	Correlations			Importance
	Zero-Order	Partial	Part	
S1	.281	.347	.032	.010
E5	.996	.996	.951	.989
E10	.189	.039	.003	.001

Drawing the desired variables with the aim of optimizing the model against their scaled changes can have a significant impact on the optimization process and correct understanding of the model. These graphs, which are also known as transformation graphs, can have different slopes based on the type of defining variable.

In Figures 58 and 60, which belong to variables S1 and E10, respectively, it can be seen that as a result of the conversion process in the target variables, the quantity of variables has taken an upward trend. This upward trend indicates that these variables can be removed from the model.

In Figure 59, it can be seen that as a result of the conversion of target variables, the quantity of variables has an almost horizontal slope, which is the reason for not removing this variable from the model.

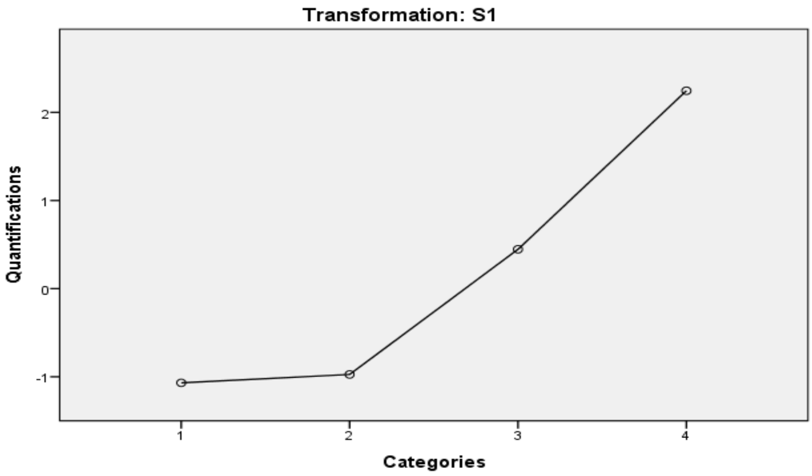


Figure 58 Diagram of transformation process per variable S1

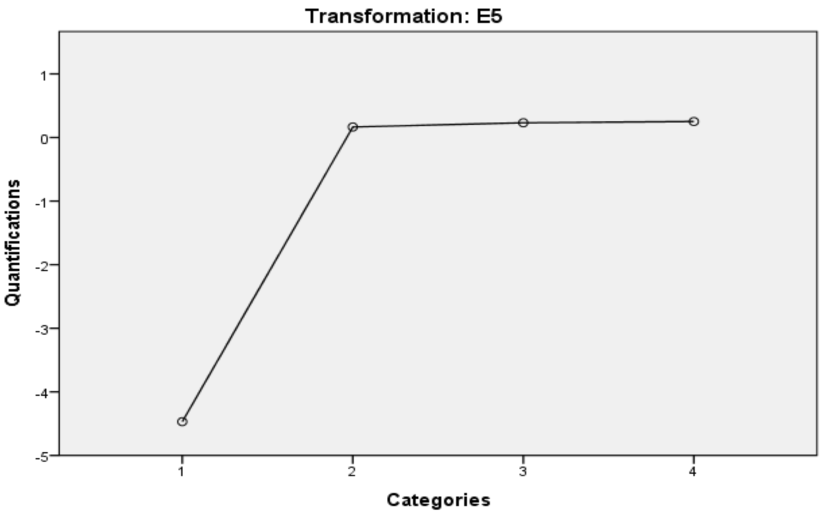


Figure 59 Diagram of transformation process per variable E5

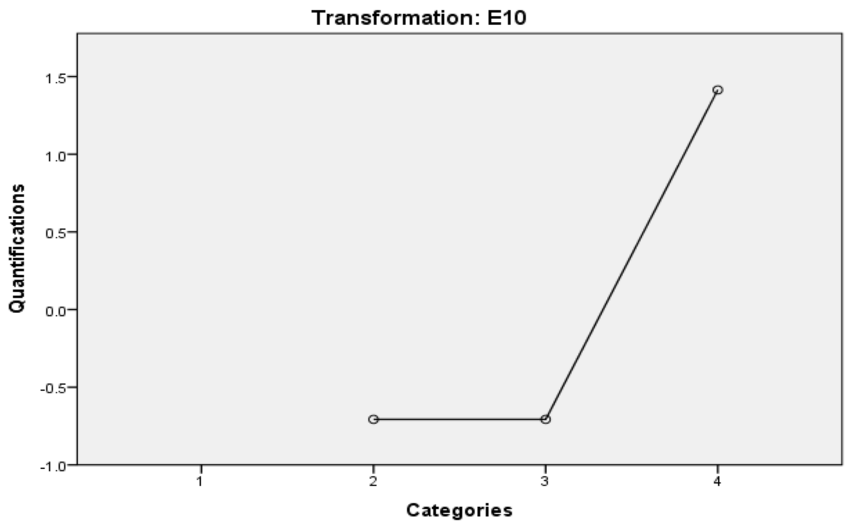


Figure 60 Diagram of transformation process per variable E10

4.7.2. Evaluation of results based on optimization

In this section, the optimization results that were performed for low-impact variables based on three factors (passenger satisfaction, crew performance, and fuel stability) are discussed. Based on the opinions of the crew and passengers, and the captain and inspector, the two variables that had the least impact were removed, and the rest of the variables were re-analyzed by the neural network. The probabilistic function predicted by the proposed neural network for different groups is analyzed in this section after the optimization process.

For this purpose, the training of the proposed network was done according to the optimization results and the removal of low-impact variables from the system, and then the frequency of data in each category was predicted. For the predictions obtained from the neural network, all error values and accuracy of the model were evaluated, and the average prediction error in the test and training stages for two variables of experience and different groups was equal to 0 and 9.4%. In Table 21, partial and overall forecast percentages for different groups (crew, passengers, captain and inspector) are presented for different layers.

Table 21 Predicted results for different groups

Sample	Observed	Predicted				
		passenger	inspector	Captain	crew	Percent Correct
Training	passenger	7	0	0	0	100.0%
	inspector	0	1	0	0	100.0%
	Captain	0	0	4	1	80.0%
	crew	0	0	0	3	100.0%
	Overall Percent	43.8%	6.3%	25.0%	25.0%	93.8%
Testing	passenger	0	0	0	0	0.0%
	inspector	0	1	0	0	100.0%
	Captain	0	0	0	0	0.0%
	crew	0	0	0	2	100.0%
	Overall Percent	0.0%	33.3%	0.0%	66.7%	100.0%

According to table 21, the percentage of prediction accuracy in the passenger group for training and test layers for 7 prediction samples is equal to 100%. Also, the percentage of prediction accuracy in the captain group to be trained is 100% for 4 prediction samples. The percentage of prediction accuracy in the ship crew group in the training and testing layers is equal to 100% for 4 and 2 prediction samples.

The probabilistic function predicted by the proposed network after performing the optimization process for the experience criterion is investigated in this section. In this section, according to the optimization results and after removing E10 and S1 variables, the input and output variables for the proposed neural network were considered.

Table 22 shows partial and overall forecast percentages for different layers. According to the table, the percentage of prediction accuracy in the variable of having previous experience in traveling with a smart ship (yes) in the training layer is equal to 87.5% for 14 prediction samples. Also, the percentage of prediction accuracy for having no previous experience in traveling with a smart ship (no) in the test layer for 3 prediction samples was equal to 100%.

Table 22 Predicted results for the experience criterion

Sample	Observed	Predicted		
		Yes	No	Percent Correct
Training	Yes	14	0	100.0%
	No	2	0	0.0%
	Overall Percent	100.0 %	0.0%	87.5%
Testing	Yes	3	0	100.0%
	No	0	0	0.0%
	Overall Percent	100.0 %	0.0%	100.0%

The overall percentage of correct prediction after applying the optimization process for the testing and training parts was obtained as 100% and 90.6%, respectively, which shows the high accuracy of the proposed neural network in predicting the variables.

Figure 61 is about testing the proposed model. Based on the evaluation of the model, it can be seen that the interest graph for the inspector group has reached the peak of 100% at a slope of 10%. The crew group has reached its peak at a 30% slope, the captain's group and the passenger group have reached their peak at a 40% slope.

Since the gain diagram of different groups is in the upper range of the diagonal line and they have reached their peak in the mentioned percentages, it indicates the successful arrangement process.

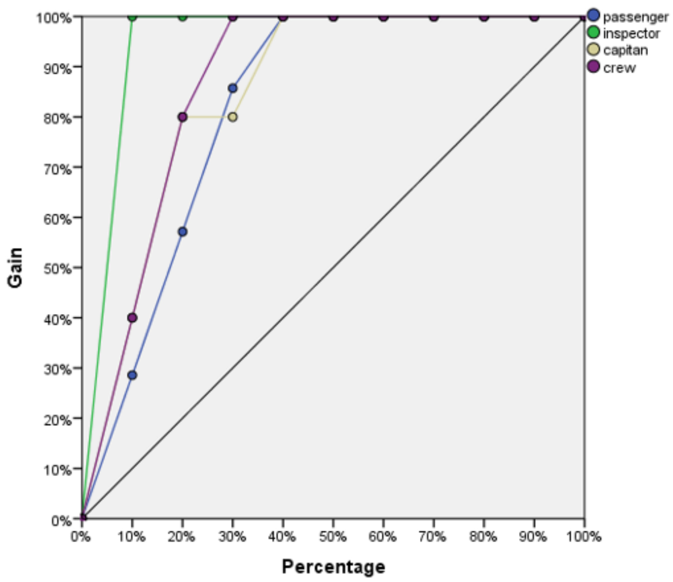


Figure 61 Profit graph for different groups after optimization

Figure 62 is the gain diagram related to the test phase of the proposed model for the variable "having previous experience of different groups in traveling by smart ship". According to the surface covered and the degree of slope (peaking at a slope equal to 10%), the successful performance of the gain plot is observed for the "Yes" variable. For passengers with no previous smart ship travel experience, the gain curve peaked at a slope of 20% and for passengers with previous smart ship travel experience, it peaked at a slope of 90%.

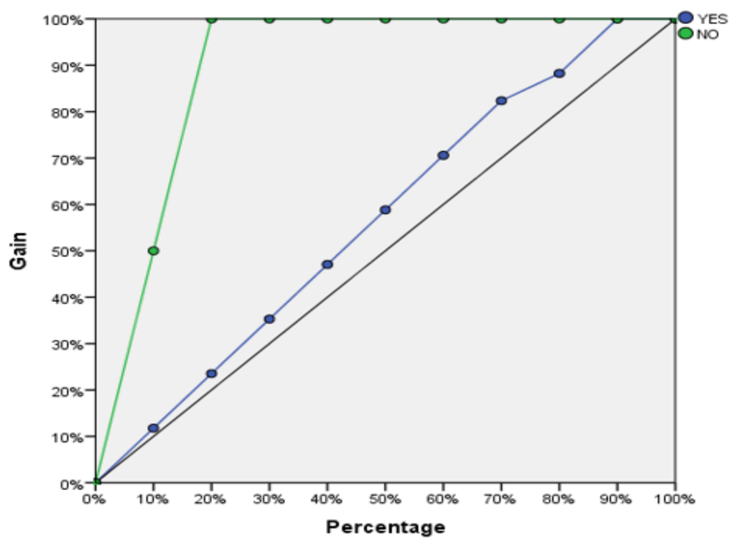


Figure 62 Profit diagram after the optimization process for the previous experience factor of different groups in traveling by smart ship

According to diagram 4-9, which is related to the testing stage of the proposed model and based on the performance of the model, it is clear that the performance of the model was acceptable for different groups. The area under the curve that is placed between the base line and the lift curve for the inspector group is more than the rest of the groups, which indicates the effectiveness of the model for this group. Also, the effectiveness of the model for the crew group was given the next priority. The effectiveness of the model for capitan and passenger groups were placed in the next priorities respectively.

In the lift diagram after optimization, it can be seen that the area under the curve between the base line and the lift curve for the captain and passenger groups has decreased. The reason for this is that the lift chart is directly related to the gain chart. Since by removing the two variables e 10 and s 1, less percentage of the available data is considered, so it should be expected that a smaller percentage of data will be included in the proposed collection.

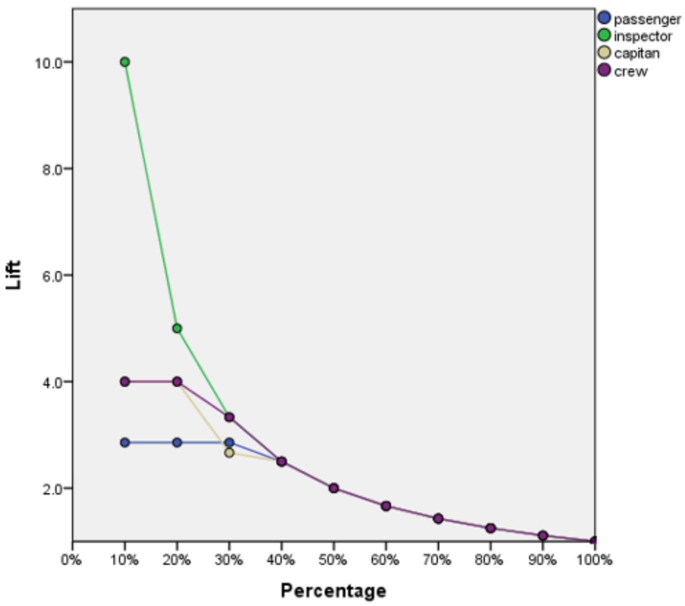


Figure 63 Lift diagram after the optimization process for different groups

In the following table, a comparison of the importance and the normalized importance of the variables for before and after the optimization process is presented. After performing the optimization process for the variables that had the least priority among the three factors, it was observed that the E7 and P5 variables had the highest priority. As a result of optimization, the average importance percentage of the variables has increased, which indicates the importance of the optimization process in the proposed system.

Table 23 Comparison of the results according to the importance percentage of model variables					
After optimization			Before optimization		
Variable	Importance	Normalized Importance	Variable	Importance	Normalized Importance
E1	.049	79.3%	E1	.033	57.5%
E2	.044	71.0%	E2	.042	72.7%
E3	.044	71.7%	P1	.038	66.8%
S2	.042	67.7%	S3	.055	95.8%
P2	.053	86.6%	E4	.046	79.7%
S3	.049	79.3%	P3	.042	72.9%
E4	.032	52.5%	S4	.055	95.1%
P3	.049	80.3%	P4	.041	72.1%
S4	.038	61.9%	E7	.045	79.2%
S5	.032	52.7%	P5	.057	100.0%
E6	.033	54.3%	S6	.041	71.1%
P4	.051	83.2%	E8	.038	66.2%
P5	.054	87.9%	P6	.041	72.3%
S6	.049	78.9%	E9	.041	72.2%
E8	.050	81.7%	E3	.036	62.9%
P1	.043	70.3%	S1	.032	56.1%
E5	.040	65.7%	S2	.048	82.9%
E7	.062	100.0%	E5	.030	52.5%
P6	.043	70.1%	S5	.054	94.2%
E9	.042	68.1%	E10	.022	37.9%
S7	.050	81.5%	S7	.037	64.8%
E11	.048	78.3%	E11	.039	67.6%
-	-	-	P2	.047	81.5%
-	-	-	E6	.039	68.4%

According to the obtained results, it can be seen that variable E7 with normalized significance equal to 100% and variables P5 and P2 with normalized significance equal to 87.9% and 86.6% respectively are more important. Also, variables S5 and E4 had the least normalized importance respectively.

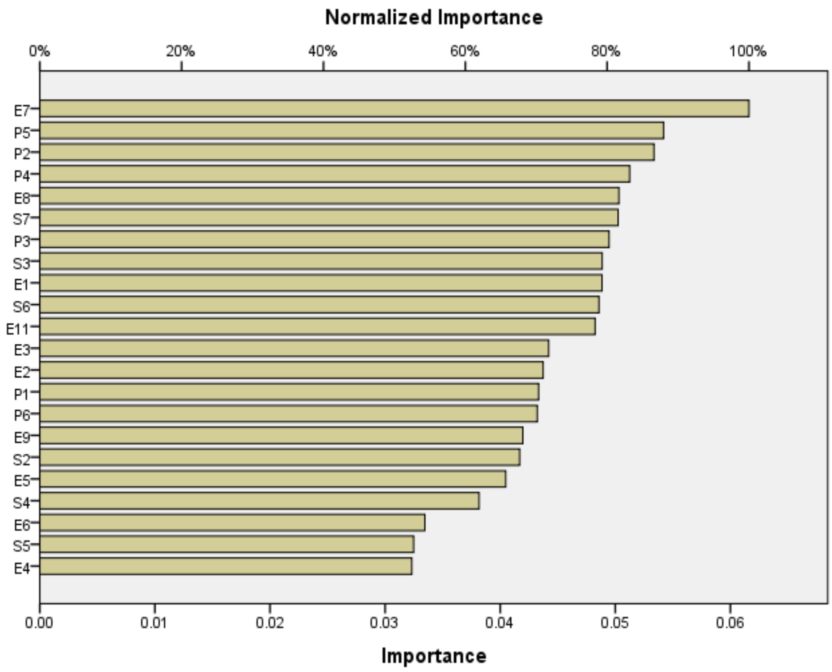


Figure 64 Independent variable importance after the optimization process

In this chapter, using neural network, the effects of smart network on marine fleet in short-distance trips were investigated. Data collection was done in the field and based on the prepared questionnaire. Completion of this questionnaire was done based on the opinions of different groups including passengers, crew, ship captain and ship inspector. After completing the questionnaire, the definition of the neural network and the components of the training and testing processes were discussed. In the process of testing and training the system, it was tried to increase the accuracy of the model as much as possible in prioritizing the variables without the least error.

Based on the results of the proposed neural network, it was found that before the optimization process, variable P5 has the highest priority in terms of different groups including passengers, crew, captain and inspector.

According to the neural network, the variables E10, S1, and E5 had the least importance, and the importance of other variables was improved by performing the optimization process. The optimization process was carried out using the regression model, based on the results, the two variables E10 and S1 were excluded from the priority of the desired variables, and the remaining variables were prioritized again.

After the optimization and training and testing of the evaluation system, it was found that according to the results, the average percentage of the importance of the variables had increased. After applying the optimization process, variable E7 had the highest priority in terms of different groups including passengers, crew, captain and inspector. Also, variables S5 and E4 were placed at the lowest level of prioritization of effective variables. Based on the results of this research, the establishment of smart network in the marine fleet from the point of view of the mentioned different groups can have a significant effect in providing the three factors.

Chapter 5

5.1. Conclusions

This research focused on empirical investigation in the field of marine fleet transportation to explore the impacts of integrating smart systems into ships on their managerial and competitive performance. The evaluation of smart ships in ports encompassed multiple perspectives, including environmental pollution, passenger satisfaction, and crew performance. The main results obtained from this research are:

(i) The utilization of a neural network, employing a machine learning algorithm, within a smart maritime transport system demonstrated its capability to accurately predict the variables that influence the triple factors. Through effective training of the neural network, it acquired the ability to analyze and forecast the key factors impacting the system's performance.

(ii) In order to enhance the competitive performance and management of the smart marine fleet, a prioritization process was conducted to determine the significance of 24 variables that impact the triple factors. These variables encompassed aspects such as passenger safety, pollution control, and ship crew performance. By prioritizing these variables, a clearer understanding was achieved regarding their respective importance and their potential influence on the overall performance and management of the smart marine fleet. This prioritization process aimed to guide decision-making and resource allocation to optimize the triple factors and drive improvements in the competitive performance and management of the smart marine fleet.

(iii) Through optimization techniques, three variables with low priority were evaluated and further analyzed. As a result, two of these variables were identified as less significant and were subsequently removed from the model. This strategic decision to eliminate these variables led to an increase in the importance and relevance of the remaining effective variables. By refining the model and focusing on the key variables, the research aimed to enhance the accuracy and effectiveness of the analysis, providing a more comprehensive understanding of the factors that significantly impact the subject under investigation.

(iv) The determination of the most influential variable and its corresponding factor in predicting the competitive and managerial performance of the smart shipping fleet was carried out in two distinct states: before and after the optimization process. By analyzing the data and employing optimization techniques, the research aimed to identify the key variable that holds the greatest significance in accurately predicting the performance outcomes. The comparison of the results before and after optimization provided valuable insights into the variable's impact on the overall performance of the smart shipping fleet, contributing to a deeper understanding of the factors that drive competitiveness and effective management within the industry.

Based on the findings of this research, it was observed that the P5 variable held the highest priority among various groups, including passengers, crew, captain, and inspectors, prior to the optimization process. This variable focused on the exchange of information with the management center and timely notification in case of potential hazards. Different groups expressed their belief that the implementation of a smart system on ships would enable prompt notifications to the management and control center during emergency situations. However, after the optimization phase, the E7 variable emerged as the top priority across all groups, including passengers, crew, captain, and inspectors. This variable pertained to ship control and management. It was widely believed among the different groups that equipping ships with a smart system had a significant impact on enhancing the overall management performance of the fleet. In terms of the three variables, namely E5, S1, and E10, which obtained the lowest priority among the triple factors, an optimization process was applied. As a result, variables S1 and E10 were removed from the model. Variable S1 was associated with selecting safe conditions in the event of a delay, while variable E10 focused on reducing fuel costs and minimizing travel time wastage. According to the perspectives of various groups, it was concluded that a smart ship, if delayed, cannot reduce the duration of the trip or exceed the permitted speed limit. Additionally, different groups expressed their belief that the costs associated with equipping, maintaining, and repairing the smart system were high, thereby imposing economic pressure on the fleet.

5.2. Answers on Research Questions’

Based on the obtained results, all the research questions have been addressed and are provided below:

Q1: Which variables are more accurate in predicting the competitive and managerial performance of the shipping fleet based on the proposed intelligent system?

Based on the results, variables E10 and E4 exhibited the highest level of accuracy, reaching 88.1%, in predicting the competitive and managerial performance of the shipping fleet.

Q2: Does a neural network based on a machine learning algorithm work properly in a smart maritime transport system?

Based on the outcomes derived from the implementation of a neural network based on a machine learning algorithm within the Smart Sea fleet, it has demonstrated remarkable success in predicting patterns.

Q3: What is the prioritization of variables in order to improve competitive performance and intelligent system management?

Based on the obtained results, variables E7 and P5 were identified as the top priorities

Q4: Which of the low-priority variables can be improved through the quality value optimization process?

Based on the findings, it was observed that among the three variables, namely E5, S1, and E10, which had the lowest priority initially, only the E5 variable remained in the model after optimization, with its normalized importance experiencing a significant increase of 13.2%. Moreover, on average, the overall system's normalized importance also witnessed a notable increase.

5.3. Research summary

This research was conducted in 5 seasons and examined the equipment of the ship with the smart system and its effect on the management and competitive performance of the marine fleet. In the first chapter, the overview of the research subject including the introduction and statement of the problem, necessity, goals and methodology of the research was discussed. In the second chapter, study records were reviewed. In this chapter, variables affecting managerial and competitive performance in the smart marine fleet were examined. Also, the disadvantages of using fossil fuel or the communication system that led to fluctuations and the advantages of the smart ship were mentioned.

In the third chapter, the description of the case and the method of data collection and the variables affecting the triple factors were mentioned, and then the questions were set. The data used in this research was collected through a questionnaire in which triple factors including passenger satisfaction, ship crew performance and pollution were considered as the main factors.

The number of questions which included 24 variables were completed by passengers, captain, crew and inspector. The age range of the people who answered the questions was between 35 and 55 years old for the inspector and captain groups. The age range for the ship crew group was between 30 and 45 years and for the passenger group between 25 and 60 years. Then all the data obtained from completed questionnaires were defined in IBM SPSS Modeler software. In the next step, the models were compared in the percentage of different tests and the percentage of the appropriate test was determined to select the models so that the models have the highest level of accuracy for prediction.

In the fourth chapter, the collected data was analyzed and effective variables were prioritized. The results indicated that before optimization, the P5 variable has the highest priority in terms of different groups including passengers, crew, captain and inspector. After identifying the variables that had the lowest priority, optimization was done. Based on neural network prediction, variables E10, S1 and E5 were the least important. Based on the results of the optimization process, the 2 channel variables E10, S1, which had the least effect, were removed from the neural network, and again the effective variables were prioritized over the triple factors. After optimization, variable E7 was the most preferred by different groups including passengers, crew, captain, and inspector.

5.4 Managerial Implications

The findings of this research have implications for various management aspects within the marine fleet. The adoption of a smart system onboard ships can provide a solution to the use of fossil fuels and subsequent environmental pollution. However, implementing such a system incurs costs, and governmental support in the form of subsidies or other facilitative measures can greatly assist the marine fleet in this transition. Another crucial consideration is the quality of the cruise experience and enhancing passenger satisfaction, as this influences their willingness to choose the same fleet for future trips. Based on the research results, equipping ships with a smart system improves travel safety and enhances management performance, ultimately resulting in a higher level of passenger satisfaction. One concern associated with employing intelligent systems is the potential impact on the ship's crew, including the fear of unemployment.

However, the research findings indicate that the crew perceives the introduction of a smart system as a supportive tool, contributing to passenger safety. Overall, the crew members express less concern about job security and prioritize a safe voyage over their own employment stability. Thus, equipping the marine fleet with an intelligent system has the potential to enhance crew performance and trip quality, leading to improved managerial and competitive performance within the marine fleet. These research findings underscore the benefits and positive impacts that can be achieved through the integration of intelligent systems in the marine industry. By focusing on safety, passenger satisfaction, and the support provided to the crew, the overall performance and competitiveness of the marine fleet can be significantly enhanced.

5.5. Limitations of the study

Like any scientific research, this study also encountered certain limitations that posed challenges to achieving the research objectives. The limitations identified in this research are as follows:

1. Difficult access to seaports equipped with intelligent monitoring and energy storage systems: The availability of suitable ports with the necessary infrastructure and technology proved to be a challenge, restricting the scope of data collection and analysis.
2. Unwillingness of some individuals to complete the questionnaire: Despite efforts to gather responses through questionnaires, a subset of participants demonstrated reluctance or declined to participate, potentially affecting the sample size and representation.
3. Age restrictions on questionnaire respondents: To ensure data accuracy and reliability, individuals under the age of 18 were excluded from the research due to the lack of relevant information or potential ethical concerns.
4. Ambiguity in certain questionnaire questions: Some respondents, including passengers and crew members, encountered difficulties in comprehending the meaning of specific questions. As a result, additional clarification was provided to enhance their understanding and ensure accurate responses.

Despite these limitations, the research team made conscientious efforts to address them and mitigate their impact on the study's validity and reliability.

5.6. Suggestions for further research

In this section, valuable suggestions are provided to researchers considering the implementation of an intelligent transportation system in their own studies. Based on the findings and insights gained from this research, the following recommendations are put forth:

1. Investigate the impact of additional variables: Researchers are encouraged to explore the influence of other factors beyond the ones considered in this study. Examples include atmospheric conditions and the role of advertisements in shaping the performance and efficiency of the intelligent transportation system.
2. Study the application of the smart system in long-term cruises: Further investigation into the use of intelligent systems in extended maritime journeys can provide valuable insights into their effectiveness and feasibility in different operational contexts.
3. Examine the triple factors in ports with land-based energy supply: It is recommended to examine the triple factors (energy, environment, and safety) in ports equipped with shore power or other forms of land-based energy supply. This analysis can shed light on the unique dynamics and opportunities associated with such ports.
4. Explore the impact of different smart systems: Researchers are encouraged to explore the effects of utilizing various types of smart systems and their specific configurations. Comparative studies can help identify the most effective and efficient solutions for specific maritime scenarios.
5. Investigate the triple factors in ports of third countries and evaluate managerial and competitive performance: Assessing the triple factors in ports located in third countries can provide valuable cross-cultural perspectives. Additionally, evaluating the managerial and competitive performance of these ports can offer insights into best practices and areas for improvement.
6. Explore the integration of smart systems in other transport fleets: Researchers are encouraged to explore the application of smart systems in other transportation domains, such as air and land fleets. This broader investigation can lead to a comprehensive understanding of intelligent transportation systems across different modes of transport.

By considering these recommendations, future researchers can enrich their studies and contribute to the advancement and optimization of intelligent transportation systems in various contexts and applications.

References

Aggarwal, C. C. (2015). *Data mining: textbook.* New York: Springer.

Alev Taskin Gumus, G. Y. (2010). Sea vessel type selection via an integrated VAHP–ANP methodology for high-speed public transportation in Bosphorus. *Expert Systems with Applications*, 4182-4189.

Ángeles Longarela-Ares, A. C.-S.-B.-L. (2020). The Influence of Economic Barriers and Drivers on Energy Efficiency Investments in Maritime Shipping, from the Perspective of the Principal-Agent Problem. *Sustainability*.

Avinash K. Dixit, B. J. (2008). *The Art of Strategy: A Game Theorist's Guide to Success in Business and Life.* W.W. Norton.

Berndt Müller, J. R. (1995). *Neural Networks.* Springer.

C. Patsios, G. A. (2012). Discussion on adopting intelligent power management and control techniques in integrated power systems of all-electric ships. *Electrical Systems for Aircraft, Railway and Ship Propulsion (ESARS)* (ss. 1-6). Bologna: IEEE.

Chang, C.-C. (2012). Marine energy consumption, national economic activity, and greenhouse gas emissions from international shipping. *Energy Policy*, 843-848.

Consulting, N. M. (2020, October). *Autonomous Ship Market*. Hentet fra nextmsc.com: https://www.nextmsc.com/report/autonomous-ships-market

David A. Aaker, C. M. (2017). *Strategic Market Management.* John Wiley.

David, F. R. (2011). *Strategic Management: Concepts and Cases.* Prentice Hall.

Dinh-Thuan Do, A.-T. L.-B. (2019). Dinh-Thuan Do, A.-T. L.-B. *IEEE*, 1-5.

DNV. (2018). *Ocean's Future to 2050*. Hentet fra dnv.com: https://www.dnv.com/oceansfuture/shipping.html

Eduardo Rivo, J. d.-F.-Á. (2012). Cross-Industry Standard Process for data mining is applicable to the lung cancer surgery domain, improving decision making as well as knowledge and quality management. *Clinical and Translational Oncology volume*, 73-79.

Edward A. Sciberras, B. Z. (2015). Electrical characteristics of cold ironing energy supply for berthed ships. *Transportation Research Part D: Transport and Environment*, 31-43.

Esri. (2006). GIS and Emergency Management in Indian Ocean Earthquake/Tsunami Disaster. *White Paper*, 1-40.

Esri. (2007). GIS Solution for Ports and Maritime Transport. *White Paper*, 1-8.

European Maritime Safety Agency. (2023). EMSA Outlook 2023. *European Maritime Safety Agency*, 1-58.

Fotis D. Kanellos, A. A.-M. (2016). Smart Shipboard Power System Operation and Management. *Inventions*, 1-14.

Frąckiewicz, M. (2023, April 25). *The Future of Artificial Intelligence in Sustainable Shipping*. Hentet fra ts2.space: https://ts2.space/en/the-future-of-artificial-intelligence-in-sustainable-shipping/

G.S. Dwarakish, A. M. (2015). Review on the Role of Ports in the Development of a Nation. *Aquatic Procedia*, 295-301.

Gaur, P. (2012). Neural networks in data mining. *International Journal of Electronics and Computer Science Engineering*, 1449-1453.

H. Zhang, L. N. (2018). Energy Efficient Subchannel and Power Allocation for Software Defined Heterogeneous Networks. *IEEE Journal*, 1-13.

Hotz, -n. (2023, January 19). *What is CRISP DM?* Hentet fra datascience-pm.com: https://www.datascience-pm.com/crisp-dm-2/

J. David Hunger, T. L. (2001). *Essentials of Strategic Management.* Ithaca: Prentice Hall.

Jae-Shik Park, T. K. (2001). Operation control of photovoltaic/diesel hybrid generating system considering fluctuation of solar radiation. *Solar Energy Materials and Solar Cells*, 535-542.

Jeetendre Narsoo, W. A. (2009). A Radio Frequency Identification (RFID) Container Tracking System for Port Louis Harbor: The Case of Mauritius. *Issues in Informing Science and Information Technology* , 127-142.

Jiri de Vos, R. G. (2021). The Impact of Autonomous Ships on Safety at Sea – A Statistical Analysis. *eliability Engineering & System Safety*, 107558.

Jun Yang, F. W. (2018). Design and Research of Ship's Intelligent Monitoring System in Wireless Network Environment. *Journa of Coastal Research*, 495-498.

Kjetil Fagerholt, M. C. (2009). A decision support methodology for strategic planning in maritime transportation. *Omega*, 465-474.

Lathia N, F. J. (2010). Mining Public Transport Usage for Personalised Intelligent Transport Systems. *IEEE 10th International Conference on Data Mining (ICDM)* (ss. 887-892). Sydney: IEEE.

Marisa Smith, U. S. (2017). EInterplay between Transportation Research measurement and management, employee engagement and performance. *International Journal of Operations & Production Management*, 1207-1228.

Michele Acciaro, H. G. (2014). Energy management in seaports: A new role for port authorities. *Energy Policy*, 4-12.

Mohammad Haseeb Zafar, I. K. (2022). An efficient resource optimization scheme for D2D communication. *Digital Communications and Networks*, 1122-1129.

Muhammad Usman, A. A. (2015). A software-defined device-to-device communication architecture for public safety applications in 5G networks. *IEEE Access*, 1649-1654.

MUNIN. (2016). Research in maritime autonomous systems Project Results and Technology Potentials. *MAritime Unmanned Navigation through Intelligence in Networks*, 1-12.

Muzaidi Othman, C.-L. S.-M. (2018). Scheduling of Power Generations for Energy Saving in Hybrid AC/DC Shipboard Microgrids. *2018 IEEE Industry Applications Society Annual Meeting (IAS)*, 1-7.

Norbert Doerry, H. R. (1996). Powering the Future with the integrated Power System. *Naval Engineers Journal*, 267-279.

Oludolapo Olanrewaju, A.-g. A. (2012). Comparing performance of MLP and RBF neural network models for predicting South Africa's energy consumption. *Journal of Energy in Southern Africa*, 40-46.

Øyvind Endresen, M. s. (2008). The Environmental Impacts of Increased International Maritime Shipping Past trends and future perspectives. 1-43.

Pete Chapman, R. K. (1999). The CRISP-DM Process Model. 1-99.

Quiroga, V. (1986). *Manual for the Estimation of First andSecond Order Regression Parameters.* Instituto Interamericano de Cooperación para la Agricultura (IICA).

Risto Jalonen, K. S. (2009). Safety Performance Indicators for Maritime Safety Management. *Helsinki University of Technology. Faculty of Engineering and Architecture.*, 1-63.

Rolls-Royce. (2016). Autonomous Ship: The Next Step. *Ship Intelligence Marine*, 1-8.

Ruoli Tang, Z. W. (2018). Optimal operation of photovoltaic/battery/diesel/cold-ironing hybrid energy system for maritime application. *Energy*, 697-714.

Sardis, T. (2023, February 5). *A brief introduction to AI and its applications in the maritime industry*. Hentet fra https://safety4sea.com/: https://safety4sea.com/cm-a-brief-introduction-to-ai-and-its-applications-in-the-maritime-industry/#:~:text=Fleet%20Management%3A%20AI%20can%20be,reduce%20downtime%20and%20save%20costs.

SINAY. (2022, March 3). *What is the Maritime Supply Chain?* Hentet fra sinay.ai: sinay.ai/en/what-is-the-maritime-supply-chain/

Suh, S. (2012). *Practical Applications of Data Mining.* Jones & Barttett Publishers.

Tashakori Abkenar, A. a. (2017). Fuel Cell Power Management Using Genetic Expression Programming in All-Electric Ships. *IEEE Transactions on Energy Conversion*, 779-787.

Trevor Hastie, J. F. (2001). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* Springer.

Veerachai Gosasang, W. C. (2011). A Comparison of Traditional and Neural Networks Forecasting Techniques for Container Throughput at Bangkok Port. *Asian Journal of Shipping and Logistics*, 463-482.

Wartsila. (2022). 7 Benefits of data-driven decision making in maritime. *Wartsila*, 1-12.

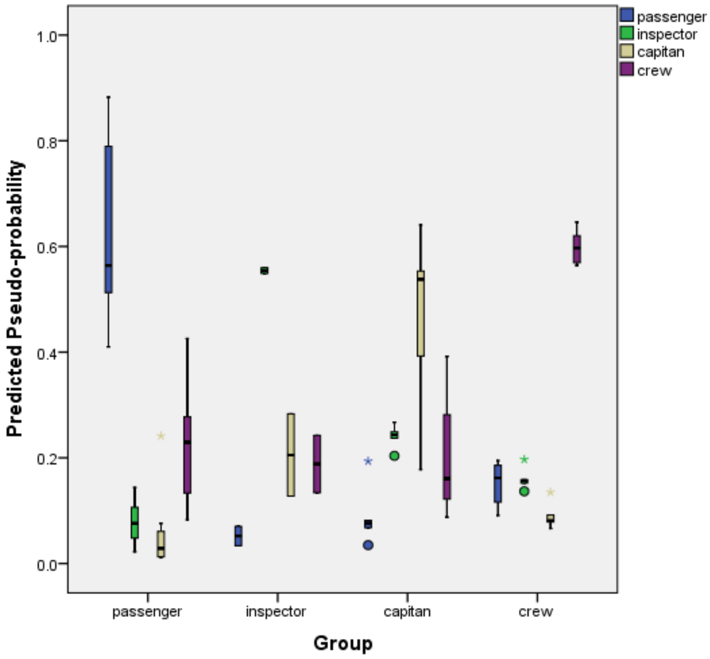
Xianjun, N. (2008). Research if dara mining based on nueral networks. *World Academy of Science, Engineering and Technology*, 381-384.

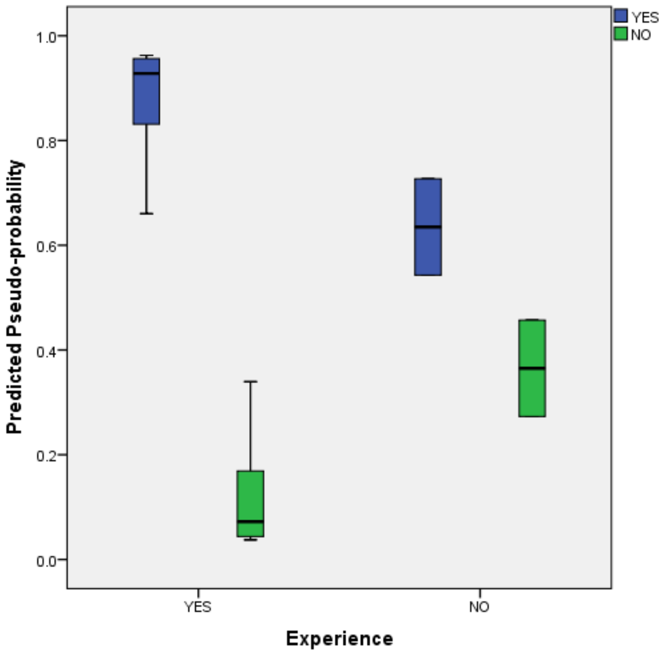
Yang, T. (2020). Intelligent Ships. I W. S. Affairs, *Maritime Law in Motion* (ss. 703-711). Springer International Publishing.

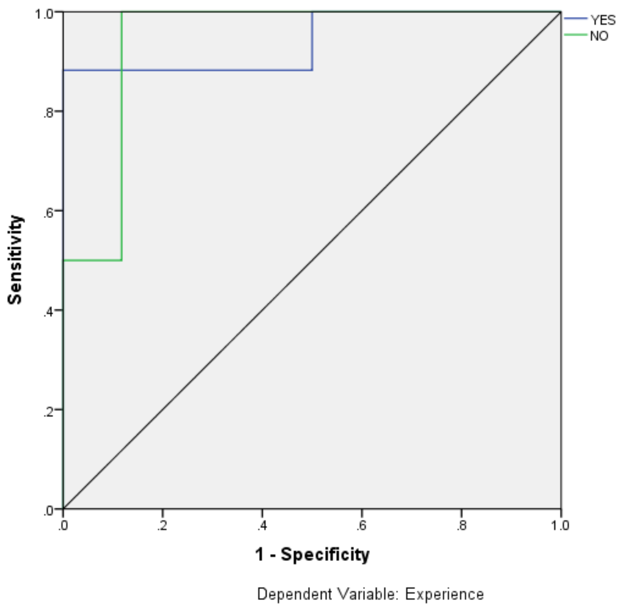
6. Appendix

The picture below is related to coding related to the optimization process is presented below.

```
CATREG VARIABLES=Experience Group S1 E5 E10
 /ANALYSIS= Experience (LEVEL=NUME) Group (LEVEL=NUME)
WITH S1 (LEVEL=NOMI) E5 (LEVEL=NUME) E10 (LEVEL=NUME)
 /MISSING=Experience (LISTWISE) Group (LISTWISE) WITH E5
(LISTWISE) E10 (LISTWISE) S1 (LISTWISE)
   E10(LISTWISE)
 /MAXITER=100
 /CRITITER=.00001
 /PRINT=R COEFF OCORR CORR ANOVA
 /INITIAL=NUMERICAL
 /PLOT=TRANS(E10 E5)(20)
 /SAVE=TRDATA RES
 /REGULARIZATION=NONE
 /RESAMPLE=NONE.
```


passenger
inspector
capitan
crew
1.0
0.8
0.6
0.4
0.2
0.0
Predicted Pseudo-probability
passenger
inspector
capitan
crew
Group


YES
NO
1.0
0.8
0.6
0.4
0.2
0.0
Predicted Pseudo-probability
YES
NO
Experience



4	1	3.00	4.00	3.00	3.20	3.25	3.00
4	1	3.00	4.00	4.00	3.10	3.08	2.71
4	1	2.00	2.00	3.00	2.40	2.18	1.71
4	1	2.00	2.00	3.00	2.50	2.74	1.71
4	1	3.00	3.00	3.00	3.27	2.91	2.57
3	1	1.00	4.00	4.00	3.00	3.18	2.43
3	1	1.00	1.00	3.00	1.83	1.64	1.29
3	1	2.00	2.00	3.00	2.70	2.65	2.29
3	1	3.00	4.00	2.00	3.10	2.82	3.29
3	1	2.00	2.00	3.00	2.67	2.36	3.00
2	1	2.00	3.00	3.00	2.67	2.64	1.86
2	1	4.00	2.00	3.00	3.40	3.52	3.43
2	1	3.00	4.00	3.00	3.20	3.36	3.29
1	2	3.00	4.00	4.00	3.57	3.55	3.57
1	1	3.00	4.00	4.00	3.73	3.92	3.57
1	2	2.00	3.00	3.00	3.17	3.20	2.43

1	1	4.00	4.00	4.00	3.27	3.36	2.29
1	1	2.00	3.00	3.00	2.63	2.55	2.43
1	1	3.00	4.00	4.00	3.50	3.45	2.86
1	1	3.00	3.00	3.00	3.68	3.48	2.86
1	1	3.00	3.00	4.00	3.67	3.54	3.29

Multi-layer neural network was used to define the network in this research.

Also, in order to assign data to different layers, ready-made functions in SPSS were used. In the section to determine the percentage of layers for testing and training and the hidden layer, prepared functions in SPSS were used.

4 1 3.0 3.00 4.00 3.00 3.00 2.00 3.00 3.00 4.00 4.00
4.00 3.00 4.00 4.00 3.00 2.00 3.00 3.00 3.00 4.00 2.00
3.00 3.00 4.00 3.50 3.18 3.00 .29755 .00436 .73847 -1.07357 -
.13103 1.61707.26599 -1.23122

4 1 2.0 3.00 4.00 3.00 3.00 2.00 3.00 4.00 4.00 4.00
3.00 2.00 2.00 3.00 2.00 2.00 3.00 3.00 4.00 3.00 4.00
4.00 3.00 2.00 3.00 3.18 2.71 .96854 -.75215 -.90788 -1.27494
1.49639-.08085 .29876 1.49971

4 1 3.0 3.00 4.00 2.00 2.00 2.00 2.00 2.00 3.00 2.00
3.00 1.00 2.00 1.00 1.00 1.00 2.00 2.00 3.00 3.00 2.00
3.00 1.00 1.00 2.50 2.18 1.71 -.82108 .53663 -1.44035 -1.67876
-.68409 .20815 -.11930 -.81769

4 1 3.0 3.00 4.00 2.00 2.00 2.00 2.00 2.00 3.00 2.00
1.00 1.00 1.00 3.00 2.00 3.00 3.00 3.00 3.00 3.00 3.00
3.00 1.00 1.00 2.50 2.64 1.71 -.27194 .61958 -2.18510 -1.23743
-.58032 -.36450 1.04588.28978

4 1 2.0 3.00 3.00 3.00 3.00 2.00 4.00 3.00 3.00 3.00
3.00 2.00 3.00 4.00 2.00 2.00 3.00 2.00 3.00 4.00 3.00

3.00 3.00 4.00 3.17 3.00 2.57 .20799 -1.01480 .50519 -.52578
.32230 1.12564-.16760 -.20751

3 1 3.0 3.00 3.00 3.00 1.00 2.00 2.00 3.00 3.00 4.00
3.00 3.00 3.00 2.00 3.00 2.00 3.00 2.00 4.00 4.00 3.00
4.00 3.00 4.00 3.00 3.18 2.43 -.70608 -.69698 -.03811 .11500 .82954
2.17958-.93742 .43824

3 1 1.0 1.00 3.00 1.00 1.00 1.00 1.00 1.00 3.00 1.00
1.00 1.00 2.00 1.00 1.00 1.00 3.00 1.00 1.00 2.00 3.00
3.00 2.00 2.00 1.83 1.64 1.29 -.60640 -1.64653 -.75208 .41057 -
2.66078-.47881 -.74323 .92754

3 1 3.0 2.00 3.00 3.00 2.00 2.00 1.00 3.00 3.00 2.00
1.00 2.00 2.00 2.00 1.00 1.00 3.00 2.00 3.00 3.00 3.00
3.00 3.00 2.00 2.00 2.45 2.29 -.58032 -.87649 -.31574 -.07676 .19554 -
.49749 -1.26055 .92834

3 1 3.0 3.00 3.00 2.00 3.00 4.00 2.00 3.00 2.00 4.00
3.00 3.00 3.00 1.00 2.00 4.00 3.00 4.00 4.00 2.00 4.00
2.00 3.00 2.00 2.50 2.82 3.29 -2.41017 1.63951-.04788 .55722
1.14706-1.16295 .67127 .94145

3 1 2.0 3.00 3.00 2.00 2.00 2.00 3.00 3.00 2.00 2.00
2.00 3.00 4.00 2.00 2.00 2.00 3.00 4.00 4.00 3.00 2.00
3.00 3.00 2.00 2.67 2.36 3.00 -1.62764 -.99080 1.24139-.16447
.94880 -.04248 .59421 -.47470

2 1 2.0 3.00 4.00 4.00 2.00 1.00 2.00 3.00 3.00 3.00
1.00 2.00 3.00 3.00 1.00 1.00 3.00 1.00 3.00 2.00 2.00
3.00 1.00 2.00 2.17 2.64 1.86 .76913 -1.51427 .42477 -.43634
.57532 -1.94820 -1.23413 -1.16421

2 1 3.0 4.00 4.00 3.00 4.00 3.00 3.00 3.00 3.00 2.00
3.00 4.00 4.00 3.00 3.00 3.00 3.00 3.00 2.00 3.00 3.00
3.00 3.00 2.00 3.17 2.82 3.43 .13398 1.218901.46911-.74021 -1.29528
-.84253 .04215 -.09702

2 1 3.0 4.00 4.00 3.00 3.00 3.00 4.00 3.00 4.00 4.00
2.00 4.00 4.00 4.00 3.00 3.00 2.00 4.00 3.00 3.00 3.00

3.00 2.00 3.00 3.00 3.36 3.29 .43983 .48591 1.46055-1.39336 -
.14865 -.52205 .69063 -.19327

1 2 3.0 4.00 4.00 3.00 3.00 3.00 4.00 4.00 4.00 4.00
4.00 4.00 3.00 4.00 3.00 3.00 4.00 4.00 3.00 3.00 3.00
4.00 4.00 4.00 3.67 3.55 3.57 1.60287.04943 .46816 .06087 .15564 -
.07606 1.78509.41661

1 1 3.0 4.00 3.00 3.00 3.00 4.00 3.00 4.00 4.00 4.00
3.00 4.00 3.00 4.00 3.00 4.00 4.00 3.00 4.00 4.00 4.00
4.00 4.00 4.00 3.33 3.82 3.57 .44154 .68662 .29085 .70233 .92526
.72369 -.36729 1.65282

1 2 2.0 2.00 2.00 2.00 2.00 1.00 3.00 2.00 4.00 3.00
3.00 3.00 3.00 4.00 4.00 4.00 4.00 3.00 3.00 3.00 3.00
3.00 3.00 3.00 3.17 3.00 2.43 .22791 -1.22902 -.25221 1.98557-
.84300 .41253 2.56137.03523

1 1 2.0 3.00 3.00 4.00 4.00 3.00 3.00 3.00 4.00 4.00
4.00 2.00 1.00 4.00 2.00 3.00 4.00 1.00 4.00 3.00 2.00
4.00 2.00 3.00 3.17 3.36 2.29 1.19932.56844 -1.70975 1.31089
1.24155-.39868 -.70795 -1.33322

1 1 2.0 2.00 3.00 3.00 2.00 3.00 2.00 2.00 2.00 3.00
3.00 2.00 3.00 3.00 3.00 2.00 3.00 3.00 3.00 3.00 2.00
3.00 2.00 3.00 2.83 2.55 2.43 -1.38665 .13387 .20935 1.18202-
.04526 .34430 -.20070 -1.86001

1 1 4.0 3.00 4.00 3.00 3.00 3.00 3.00 3.00 4.00 4.00
4.00 2.00 3.00 4.00 3.00 3.00 4.00 2.00 3.00 3.00 2.00
4.00 4.00 4.00 3.50 3.45 2.86 .86683 1.53893-.58905 .53261 -.65411
.90301 -.52586 -.95129

1 1 3.0 3.00 3.00 4.00 3.00 2.00 3.00 3.00 4.00 3.00
3.00 3.00 3.00 3.00 2.00 3.00 4.00 3.00 3.00 2.00 3.00
3.00 3.00 3.00 2.83 3.18 2.86 .65878 .06181 .45099 .99599 .27480 -
1.59346-.23418 -.18785

1 1 3.0 4.00 3.00 3.00 3.00 4.00 3.00 3.00 4.00 3.00
4.00 4.00 4.00 4.00 3.00 4.00 3.00 1.00 3.00 3.00 4.00

4.00	4.00	4.00	3.17	3.64	3.29	.59600	1.17704.97932	.74856	-1.06968
.49409	-1.45714		1.38827						