Alessandro Boveri

APPROACHES TO SHIPBOARD POWER GENERATION SYSTEMS DESIGN AND MANAGEMENT

Probabilistic approach to load prediction and system optimal design, sizing and management

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Supervisors
Federico Silvestro
Paola Gualeni

Candidate
Alessandro Boveri

University of Genoa
Department of Electrical, Electronic, Telecommunication Engineering, Naval Architecture and Marine Engineering – DITEN
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There is a powerful agent,
obedient, rapid, easy,
which conforms to every use,
and reigns supreme onboard my vessel.
Everything is done by means of it.
It lights, warms it, and is the soul of my mechanical apparatus.
This agent is electricity.

Captain Nemo, 20000 leagues under the sea
Jules Verne, 1870

ABSTRACT

This doctoral thesis presents new ideas and formulations on shipboard power system sizing and management. The main motivation behind this work is to fill, at least in part, the current technological and mythological gap between land and marine applications, concerning the sizing and management of power systems. This gap is the result of several changes regarding both the electric and marine applications. Two of these are, for example, the recent increase of electric power installed on board modern vessels and recent development of technologies for land microgrids. In this context, it should be noted that, also the modern ships are comparable to land microgrids, where the generation and loads are close in space and the on board power system may work either islanded or connected to the land grid. Nowadays, microgrids are a hot topic in electric engineering, with a constant development of novel approaches for both their sizing and management. On the other hand, considering the increase in the power installed on board ships, the traditional methods developed in the last century to size and manage these systems have shown increasing limitations and inaccuracies. This results in oversized power generation systems, low performances and high level of air and sea pollution due to ships activities. To overcome these problems and criticalities, this work presents a probabilistic approach to load prediction, which may increase the flexibility of the power system design and allow a significant reduction in the total power installed. Moreover, the traditional method to size the diesel generators, based on satisfying the maximum load, it is revised with the formulation of an optimal problem, which can consider as input either the results of the traditional method to load prediction or those obtained applying the probabilistic one. Finally, due to the recent introduction in land microgrids of energy storage system, which may cover the power fluctuations due to renewable resources, allow a better management of energy and increase the quality of service, an optimum method is developed and described in order to select, size and manage these systems on board ships.

Sommario

Questa tesi di dottorato presenta nuove idee e formulazioni su dimensionamento e gestione del sistema di alimentazione di bordo. La motivazione principale alla base di questo lavoro è di colmare, almeno in parte, l'attuale divario tecnologico e mitologico tra applicazioni terrestri e marine, per quanto riguarda il dimensionamento e la gestione dei sistemi energetici. Questo divario è il risultato di numerosi cambiamenti riguardanti il mondo elettrico e quello navale. Due di questi sono, ad esempio, il recente aumento della potenza elettrica installata a bordo delle moderne navi e il recente sviluppo di tecnologie per le microreti terrestri. In questo contesto, va notato che, anche le navi moderne sono paragonabili alle microreti terrestri, dove la generazione e i carichi sono vicini nello spazio e il sistema di alimentazione a bordo può funzionare a isola o collegato alla rete terrestre. Al giorno d'oggi, le microreti sono un tema importante nell'ingegneria elettrica, con uno sviluppo costante di nuovi approcci per il loro dimensionamento e gestione. D'altra parte, considerando l'aumento della potenza installata a bordo delle navi, i metodi tradizionali sviluppati nel secolo scorso per dimensionare e gestire questi sistemi hanno mostrato limitazioni e inesattezze crescenti. Ciò si traduce in sistemi di generazione di energia sovradimensionati, in basse prestazioni e alti livelli di inquinamento atmosferico e marino dovuto alle attività delle navi. Per superare questi problemi e criticità, questo lavoro presenta un approccio probabilistico alla previsione del carico, che può aumentare la flessibilità della progettazione del sistema di alimentazione e consentire una significativa riduzione della potenza totale installata. Inoltre, il metodo tradizionale per dimensionare i generatori diesel, basato sulla soddisfazione del carico massimo, viene rivisto con la formulazione di un problema ottimale, che può considerare come input sia i risultati del metodo tradizionale per caricare la previsione sia quelli ottenuti applicando il probabilistico uno. Infine, a causa della recente introduzione nelle microreti terrestri del sistema di accumulo dell'energia, che può coprire le fluttuazioni di energia dovute alle risorse rinnovabili, consentire una migliore gestione dell'energia e aumentare la qualità del

servizio, viene sviluppato e descritto un metodo ottimale per selezionare, dimensionare e gestire questi sistemi a bordo delle navi.

CONTENTS

NOMENCLATURE

List of Acronymis

AC	*Alternative Current*
AES	*All Electric Ship*
ANNs	*Artificial Neural Networks*
AR	*Auto Regressive*
ARMA	*Auto Regressive Moving Average*
B	*Ship's Breath*
CA	*Contingency Analysis*
CDFs	*Cumulative Distribution Functions*
CR	*Cross Over Rate*
DC	*Direct Current*
DDP	*Dynamic Dispatch Problem*
DGs	*Diesel Generators*
DLF	*Dual Fuel Engine*
DMS	*Demand Side Management*
DP	*Dynamic Positioning*
DoD	*Energy Storage System Depth of Discharge*
DWT	*Dead Weight Tonnage*
EA	*Evolutionary Algorithms*
EEDI	*Energy Efficiency Design Index*
EEOI	*Energy Efficiency Operating Index*
ED	*Economic Dispatch*
ELL	*Electric Load List*
EMS	*Energy Management System*
EPLA	*Electrical Power Load Analysis*
ESS	*Energy Storage System*
FL	*Fuzzy Logic*
FOC	*Fuel Oil Consumption*
FxS	*Fixed Speed Diesel Generator*

GA	*Genetic Algorithms*
GAMS	*General Algebraic Modelling System*
GHG	*Greenhouse Gas*
GLF	*Generator Load Factor*
HVAC	*Heat Ventilation and Air Conditioning*
IAS	*Integrated Automation System*
IC	*Installation Costs*
IES	*Integrated Electric Ship*
ILS	*Intelligent Load Shedding*
IMO	*International Maritime Organization*
LFs	*Load Factors*
LNG	*Liquefied Natural Gas*
L_{OA}	*Ship's Length Over All*
LV	*Low Voltage*
LTLF	*Long – Term Load Forecast*
MA	*Moving Average*
MC	*Mission Costs*
MCS	*Monte Carlo Simulation*
MDO	*Marine Diesel Oil*
MEPC	*Maritime Environmental Protection Committee*
MLE	*Maximum Likelihood Estimation*
MILP	*Mixed Integer Linear Programming*
MINLP	*Mixed Integer Non-Linear Programming*
MV	*Medium Voltage*
MVDC	*Medium Voltage Direct Current*
MTLF	*Midterm Load Forecast*
NLP	*Non-Linear Programming*
PDFs	*Probability Density Functions*
PMS	*Power Management System*
PN	*Population Number*
PRA	*Probabilistic Risk Analysis*
PSD	*Power System Dispatch*
PSV	*Platform Supply Vessel*
PTI	*Power Take In*
PTO	*Power Take Off*

PV	*Photovoltaic*
RES	*Renewable Energy Sources*
SEEMP	*Ship Energy Efficiency Manage Plan*
SFOC	*Specific Fuel Oil Consumption*
SoC	*Energy Storage System State of Charge*
SOLAS	*Safety of Life at Sea*
SSES	*Ships System Engineering Station*
STLF	*Short - Term Load Forecasting*
SWBS	*Ship Work Breakdown Structure*
T	*Ship's Draft*
TC	*Total Costs*
UC	*Unit Commitment*
VFDs	*Variable Frequency Drives*
VrS	*Variable Speed Diesel Generator*
V_{SHIP}	*Ship Speed*

List of Symbols

α	*Probability to Reject the Null Hypothesis*
A_V	*Surface Internal Spaces*
β	*Probability to Accept the Null Hypothesis if the Alternative is True*
β_1	*Skewness*
β_2	*Kurtosis*
C_c	*Energy Storage System Current Rate in Charge*
C_d	*Energy Storage System Current Rate in Discharge*
C_i	*Diesel Generator's Installation Cost*
$\mathrm{C}_{\mathrm{I}_{\mathrm{ESS}}}$	*Energy Storage System Installation Cost*
C_{in}	*Penalty Function Known Values*
C_{inst}	*Energy Storage System Installation Cost*
$\mathrm{C}_{\mathrm{I}_{\mathrm{INV}}}$	*Inverter Installation Costs*
c_p	*Specific Heat*
C_{R}.	*Replacement Costs*

η	*Generator Efficiency*
$\mathrm{DG}_{\mathrm{min}_{\mathrm{down}}}$	*Diesel Generator's Minimum Time Down*
$\mathrm{DG}_{\mathrm{min}_{\mathrm{up}}}$	*Diesel Generator's Minimum Time Up*
DoD_{avg}	*Energy Storage System Average Depth of Discharge*
DoD_{max}	*Energy Storage System Average Maximum Depth of Discharge*
ΔT	*Difference in Air Temperature*
dt	*Simulation's Time Step*
E_{ESSmax}	*Energy Storage System Maximum Size*
E_{ESSmin}	*Energy Storage System Minimum Size*
E_{ESSnom}	*Energy Storage System Nominal Size*
$E_{exchanged}$	*Energy Storage System Total Energy Exchanged*
FC	*Fuel Cost*
f_{ij}	*Deterministic Factors*
$f_{I\Phi}(i,\varphi)$	*Current and Phase Joint Probability Density Function*
$f_{p_{load}}$	*Operating Load Probability Density Function*
G	*Number of diesel Generators Installed*
H_0	*Null Hypothesis*
H_1	*Alternative Hypothesis*
h_{scott}	*Number of Bins from Scott's Rule*
K_d	*Diversity Factor*
k_G	*Total Heat Transfer Coefficient for Surface A_G*
Ks	*Coincidence Factor*
Ku	*Demand Factor*
k_V	*Total Heat Transfer Coefficient for Surface A_V*
$L(\theta)$	*Likelihood Function*
LF_{ij}	*Load Factor*
m_{in}	*Penalty Function Angular Coefficient*
m_{water}	*Water Mass Flowing*
μ	*Mean of a Probability Distribution*
N_{class}	*Number of Classes*
$N_{C_{Daily}}$	*Energy Storage System Daily Cycles*

$N_{C_{Tot}}$	*Energy Storage System Number of Charge and Discharge Cycles in Life*
n_{ij}	*Number of Devices in Function*
$N_{replacement}$	*Energy Storage System Number of Replacement in Ship's Life*
$N_{Service_{Daysy}}$	*Energy Storage System Total Number of Service Days*
$P_{absorbed}$	*Power Absorbed*
$\mathrm{P}_{\mathrm{ESS_j}}$	*Energy Storage System Power Delivered*
P_{ESSc}	*Energy Storage System Rated Power in Charge*
P_{ESSd}	*Energy Storage System Rated Power in Discharge*
P_G	*Generator Rated Power*
P_G^{MAX}	*Generator Maximum Power*
P_G^{MIN}	*Generator Minimum Power*
$P_{gen_{ij}}$	*Power Delivered by the i^{th} Generator at the j^{th} Time Step*
$P_{gen_{ijn}}$	*Penalty Function Power Limits*
P_{INV}	*Inverter Rated Power*
P_{load}	*Load Power*
p_{load}	*Random Variable Operating Load*
P_{loss}	*Power Wasted in System's Loss*
P_{nom_n}	*Penalty Function Rated Power*
$P_{ol_{ij}}$	*Operating Load Power*
P_{rated_i}	*Rated Power*
P_{Tot_j}	*Total Operating Load in j^{th} Scenario*
Q	*Heat Exchanged*
SoC_0	*Initial State of Charge*
SoC_f	*Final State of Charge*
S_n	*Expression of the Exit Neuron*
SR	*Spinning Reserve Limit*
σ	*Variance*
t	*Time Step*
u_{ij}	*State Of Generator i^{th} at j^{th} Time Step*
UF	*Utilization Factor*

v_{ij}	*Diesel Generator Start-Up State*
w_{ij}	*Diesel Generator Shutdown State*
w_{LF}	*Diesel Generator Load Factor Weight*
$\mathrm{w}_{\mathrm{P}_{\mathrm{gen}}}$	*Diesel Generator Power Delivered Weight*
w_{SoC}	*Energy Storage System State of Charge Weight*
w_{Su}	*Diesel Generator Number of Start-ups Weight*
Φ	*Heat Transmission Losses*
φ	*Current Phase*
z_{ijn}	*Penalty Function States*

1 INTRODUCTION

The first application of a simple Direct Current (DC) motor on board a boat was in the late 1830s by Moritz Hermann von Jacobi [1]. In fact, he performed some experiments to verify the possibility to adopt such electrical motors to allow the transportation of passengers. Unfortunately, he did not succeed, due to the very low power supplied by the motor itself (about 1 kW) with a corresponding boat's speed of only 4 knots.

Afterwards, the first employment of a Low Voltage (LV) DC power system on board ships was in the 1880 when, in order to power 120 incandescent lights, Henry Villard ordered the installation of such system for his company's new steamship (i.e. SS Columbia) [2]. Going through the so-called *"war of current"* between Edison on one side, Tesla and Westinghouse on the other one [3], the power system, especially the ones in Alternative Current (AC), has become intensively employed on-board ships. Therefore, from its birth upon todays, marine power systems have growing in complexity and size. This is also a consequence of the massive use of power electronics devices, commercially available from the 1980s, which allow to cope with different power requirements (i.e. voltage, frequency and AC/DC). In this perspective, the conversion of many users from the compressed air or hydraulic powering systems to the electrical vector has been possible and convenient. Therefore, it is possible to note that electrical power systems have been increasingly used since the beginning of the 19th century and, nowadays, their applications are always increasing in importance and development on board ships.

1.1 Background

Basically, each ship requires a lot of power for the propulsion and, depending on the category of ship, significant power for service devices. Accordingly, from a mechanical and electrical power system point of view, ship can be grouped as follows [4], [5]:

- *Mechanical propulsive ship*, this category of ships had installed very large mechanical motors to supply enough power to the propellers that move the ship. The electrical load is covered, usually, with small diesel generators. This is one of the most traditional ship design and widely adopted for many years.
- *Hybrid ship,* this presents a configuration similar to ships with a mechanical propulsion system (i.e. they have installed large mechanical motors for the propulsion and diesel generators for the electric load). On the other hand, they have installed a Power Take In (PTI) and/or Power Take Off (PTO) system in order to supply power to the propulsion from the electrical power system and absorb power from the propulsion system to the electrical one, respectively. This configuration has allowed many merchant ships to optimize both the generation and the costs when the ship is in navigation (e.g. many bulk carrier ships are configured in this way). In fact, due to the possibility to run the mechanical motor close to its most efficient point and, at the same time, to burn low priced fuel (e.g. heavy fuel oil instead of the marine diesel oil required by the diesel generators) it is possible to supply electrical energy to the power system (i.e. PTO system).
- *Integrated electric ship,* for this category of ship, both the propulsion and the service power is supplied by the electric power system. Considering the navy ships, todays many of these categories are moving towards this

configuration. This configuration allows a good reliability and flexibility of the power system, in addition to the generation system optimization.

- *All Electric Ship (AES),* converting each user on board, which was powered by compressed air, steam or hydraulic system to the electrical power system it is possible to talk of AES. Such a configuration allows many management, design and reliability solutions. In fact, AES are even more similar to a land based microgrid[1] in islanding mode, where generation and loads are close in defined boundaries.

Considering all these categories, it is possible to highlight an increasing in complexity of their power systems. Moreover, a look forward in the next future of the marine power systems allows introducing the following technologies [4], [5]:

- *Medium Voltage (MV) AC power generation,* this is a technology already mature and used on board new ships. It presents good levels of reliability, controllability and efficiency.
- *High Frequency AC (HFAC) power generation,* this configuration considers a generation with frequency between 60 and 400 Hz. The distribution voltage can be both at 4.6 or 13.8 kV. HFAC has advantages such as the use of lighter transformers, minimization or elimination of filters for harmonics, galvanic isolation between subsystems and improved acoustic performances (e.g. estimated to be close to 6.5 times less than in 60 Hz systems). On the other hand, HFAC generation presents also many challenges and needs other years to be used on board.
- *MVDC power generation,* the main reasons to introduce this technology are the possibility to decouple the prime mover's speed from the frequency of the bus enabling the optimization of each generators, easier integration of the renewables on board (e.g. photovoltaics, wind, storage and fuel cells), paralleling of generators with only voltage matching

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[1] *A microgrid is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode [6].*

instead of voltage and frequency and other advantages. On the other hand this is a technology not already mature and reliable, in fact, we face problem with the traditional fault detection, need of a grounding strategy, the development of power quality standards and a lack of both standards, technologies and knowhow.

However, independently from the technology applied to design on board power systems, the first design phase for a shipboard power system is to predict the load. As in land networks with the advent of renewable energy sources, the conversion of the users on board from the traditional powering systems (e.g. compressed air, steam and hydraulic) to the electric power has increased the uncertainties in the design and management of the power system.

From a marine point of view, these uncertainties are not related to renewable generation but rather to the load prediction. In fact, the AES's load is a combination of propulsion (i.e., bound to both ship speed and marine weather conditions) and services loads (i.e. related to human behaviour, ship's operational condition and meteorological conditions).

A good prediction of the electrical load is essential in design phase in order to correctly select and size the generation, distribution and transformation, which are the core of the on board power system.

This issue is even more central in the field of naval vessels, where it is required a considerable survivability of the system, as well as in the context of passenger ships, where the safety and comfort of passengers are imperative.

As it happens in terrestrial applications, it seems to be useful to reason in probabilistic terms, in order to incorporate all these uncertainties in the design process and allow a wider range of possible design choices. Furthermore, after the power system optimum design, also an optimum management of the generation and load is essential.

1.2 Aim of the Thesis

As already stated, an accurate and reliable prediction of the electrical load is essential in ship design phase, where the generation, distribution, transformation and protection systems are sized and selected. Together with the continuous increase of the electrical power installed for both generation and services on board ships, uncertainties in load prediction become even more significant and disruptive. In this context, an inaccurate prediction may cause an oversizing of the whole power system, with the consequence of generators that work far from their optimal efficiency point, increased costs of installation and maintenance and, last but not least, a more significant environmental footprint of the ship.

On the other hand, an under sizing of the system is also possible but not recommended. In fact, consequences of a under sizing are overloading of the generators (i.e. which causes an increase in costs and a damages), frequent blackouts and again an increase in costs and in the environmental impact of the ship.

The principal uncertainties in the power system design comes from the human behaviour, the weather conditions and from the increased number of users supplied from this system on board modern ships. Furthermore, despite the considerable benefits in ship management phase and the flexibility that provide the adoption of Variable Frequency Drivers (VFDs), these have complicated the load prediction of the users driven by this technology.

In this perspective, this dissertation deals with probabilistic approaches in order to evaluate the electrical load in different phases of the ship design and the optimal size and selection for the power generation system.

Then, in order to face also the problem of the uncertainties in ship's management and the optimum managing of both the generation system and loads, several approaches are proposed in this work.

In fact, many Energy Management Systems (EMS) or Power Management Systems (PMS) used today in the marine applications are fairly simple. This is mainly due to the relatively low number of units usually installed on board and low variety of prime mover types and fuels used [7]-[8].

The extensive knowledge in *“inland”* power generation and distribution has found limited use in the marine application, until now. While the methods of Unit Commitment (UC), Economic Dispatch (ED) and Contingency Analysis (CA) have been extensively used for decades in terrestrial power systems, their applicability to traditional shipboard systems has been limited [9]. Moreover, also approaches such as Intelligent Load Shedding (ILS), Load Shifting (LS) or Demand Side Management (DSM) are not already implemented on board ships [10]-[12]. Nevertheless, at least in principle, these methods may provide potentially a significant operational cost reduction, along with improvements in planning and intelligent handling of the power plant.

The mentioned research tasks mainly target commercial vessels such as passenger ships or naval vessels, due to the significant amount of electrical power and users installed.

1.3 Main Contributions

The main contributions found in this thesis are summarized below:

- The probabilistic approach to EPLA has been formulated and validated in Chapter 3. Among the number of methods proposed to characterise statistically the electric loads on-board, depending on the input information available, the tests performed have demonstrated that all these method are efficient and reliable. Considering the probabilistic approach to EPLA, the application to the case studies has shown the effectiveness and reliability of this methodology to predict the power demanded to the power generation system.

- Considering the results obtained applying the probabilistic EPLA, an optimum problem has been formulated in Chapter 4 in order to design and size in the more flexible and economic way the diesel generators on-board. This method has also been tested by using the same two case studies considered to test the probabilistic EPLA. Results shown sensible reductions in costs (e.g. close to 50% in a best-case scenario) and total power installed for the generation.

- In Chapter 5, an algorithm to optimally select, design and manage an energy storage system on-board ship has been presented and validated. In this case, the tests performed on two case studies (e.g. a ferry and a platform supply vessel) demonstrated the effectiveness of installing a storage system to mitigate the power fluctuation and allow a more flexible energy management. Moreover, the optimal management of both the energy storage and the diesel generators allows a significant reduction in management costs (e.g. up to 30% in a best-case scenario) and in GHG emissions.

The proposed methodologies have been implemented by adopting MATLAB and GAMS (General Algebraic Modelling System) in order test and validate the formulations.

1.4 List of Publications

This Ph.D. has originated the following scientific publications on journals and conferences.

Transaction and Journal papers:

A. Boveri, F Silvestro, M. Molinas, E. Skjong, "Optimal Sizing of Energy Storage Systems for Shipboard Applications", *submitted in IEEE Transaction on Energy Conversion*, January 2018. (SUBMITTED)

A. Boveri, F. D'Agostino, A. Fidigatti, E. Ragaini and F. Silvestro, "Dynamic Modeling of a Supply Vessel Power System for DP3 Protection System," in *IEEE Transactions on Transportation Electrification*, vol. 2, no. 4, pp. 570-579, Dec. 2016. doi: 10.1109/TTE.2016.2594156

P Gualeni, **A P Boveri**, F Silvestro, A. Margarita, "Decision Support System for Power Generation Management for an 110000+ GRT Cruise Ship", *RINA International Journal of Maritime Engineering (IJME)*, vol. 158, Part A2, pp.A163-A171, September 2016.

Conference papers:

A. Boveri, P. Gualeni, D. Neroni, F. Silvestro, "Stochastic Approach for Power Generation Optimal Design and Scheduling on Ships", *Innovative smart Grid conference (ISGT) Europe*, Torino, 2017, pp. 1-6.

A P Boveri, F Silvestro, A Panzera, I Crocicchia, R Lodde, "Ship's Central Cooling System Live Performance Optimisation And Modeling", *RINA Smart Ship Technology Conference,* 24-25 January 2017, London (UK).

A. Boveri, F. Silvestro and P. Gualeni, "Ship electrical load analysis and power generation optimisation to reduce operational costs," *2016 International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*, Toulouse, 2016, pp. 1-6. doi: 10.1109/ESARS-ITEC.2016.7841422

A P Boveri, P Gualeni, F Silvestro, "Stochastic Electrical Plan Load Analysis for Increasing Flexibility in Electrical Ship Systems", *RINA Smart Ship Technology Conference,* 26-27 January 2016, London (UK).

National journal paper:

A Boveri, F D’Agostino, F Silvestro, E Palmisani, F Viacava, “Sistemi Di Accumulo A Bordo Nave: Fattibilità E Prospettive Di Impiego Per Il Trasporto Ecologico”, *focus AEIT Luglio-Agosto 2017*.

1.5 Awards and Scientific Recognitions

Winner of the “**Ian Telfer Prize, 2017**” for the paper *“Decision Support System for Power Generation Management for an 110000+ GRT Cruise Ship”*, which is awarded annually by the Royal Institution of the Naval Architects for the best paper published in the Transactions by an author aged 35 or under, on the subject of the marine environment.

2 STATE OF THE ART ON LOAD PREDICTION

The design of a complex system such as a ship requires and involves many different disciplines and knowledge of engineering. Ship design is not a straightforward approach that involves input information, application of methods and final results. In fact, the overall design of a ship can be seen as a spiral linear iterative approach (i.e. this is called design spiral in maritime engineering). This approach requires that each step in the design have to be repeated at the end of one cycle of the spiral [13]. In this context, the Electrical Power Load Analysis (EPLA) is one of the most important step in ship design. The EPLA consists in a long-term prediction of the power demanded by the electrical users installed on-board. As already introduced, the ship users powered by the power system depend on the configuration of the ship itself.

Traditionally, the mechanical propulsive ship has a power system for service devices of small size, if compared with the propulsion system. In fact, the users powered by the on board power system are, for this kind of ship, the auxiliaries such as pumps, compressors, heaters and the lighting system. Historically, this configuration was the most adopted in marine applications. Actually, the idea was to divide the power generation between the one required for the ship propulsion and the one required for services. Other kind of power drivers such as the air-compressed and hydraulic systems were often used for many users requiring high values of power.

Nowadays, many ships are designed and built with a deeper penetration of the electrical vector such as power drivers. In this context, the majority of the users installed on board are driven by the power system. Recently, also thanks to power electronic devices improvement, the power required for the ship propulsion is supplied by the power system as well. In this perspective, it is possible to talk of Integrated Electric Ship (IES) configuration or All Electric Ship (AES), when all the users and services are driven by the power system.

The ever-increasing and ever-penetrating conversion of the on board users to electric power has made the whole system more complicated than in the past in both design and management of the ship. In fact, there is an increase of the uncertainties related to the load prediction for the power system. In the past, these uncertainties were usually covered oversizing the systems. Differently, today it is required by both the international normative and the stakeholders to improve the efficiency of the ships both in design and in operation. In this perspective it is no more possible to design a ship considering only the safety aspects (i.e. that is always of primary importance) or the owners income. As it is explained in the following paragraph, the first step to efficiently design the on-board power system is to correctly predict the power demand.

2.1 Long-term load prediction for land based microgrids

In the context of AES or IES, it is possible to talk about marine microgrids. In fact, there are similar aspects to those faced for land based microgrids, such as the interconnection of loads and energy resources in a relatively small area, the ship can be connected to the onshore grid with the so called ship to shore configuration and can also operates in islanding mode (i.e. which is the normal configuration of the on-board power system). Moreover, there is also the possibility of introducing distributed energy resources (e.g. photovoltaics, wind turbine, fuel cells and thermal energy sources) to follow the distributed generation approach used also in land applications.

In land microgrids, one of the major sources of uncertainties is the load prediction. This depends on several factors such as the human behaviour, the number of consumers, the hourly price of electricity, and weather conditions [14]. Another source of uncertainties is the level of renewable resources penetration in the microgrids. In fact, depending mainly on weather conditions, renewable resources does not follow a deterministic path in daily operations. Therefore, an accurate forecast of the power delivered by these sources on site is also challenging and affected by the weather forecasts. However, in land applications, there are many sources of information on the power demanded by the consumers, mainly thanks to measurement systems installed in buildings and at each node of the grid.

2.1.1 Forecasting methods classification

According to the reference time horizon, load forecast methods can be classified as short term, midterm, and long term [15]-[16]. Short-Term Load Forecasting (STLF) methods are considered over an interval ranging from an hour to a week. These are important for different functions in electrical engineering and grid management such as the unit commitment, economic dispatch, energy transfer scheduling, and real-time control. The Midterm Load Forecast (MTLF) methods, considered ranging from 1 month to 5 years and sometimes 10 or more years, are used by the utilities to purchase enough fuel and for the calculation of various electricity prices. Finally, Long–Term Load Forecast (LTLF) methods that cover from 5 to 20 years or more are applied by planning engineers and economists to plan for the future expansion of the system, type and size of generating plants and transmission lines, that minimize both fixed and variable costs [17]. Several and different factors affecting each methodology should be considered, such as time factors, weather data, and possible customers' classes for STLF. Otherwise, for the medium-and long-term forecasts it is required to take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, the appliance sales data, and other factors.

Actually, most of the electric-load forecasting approaches are dedicated to short-term forecasting but not as much for the long-term or intermediate-term load forecasting [15]. It seems evident that forecasting methods are a systematic process, which depend mainly on the time horizon considered. Usually, the load-forecasting methods applied in land applications can be classified as deterministic or probabilistic methods. A third approach can be seen as a combination of the previous ones. These categories are mathematically based on extrapolation, correlation, or a combination of the previous, accordingly.

Another possible division over the forecasting methodologies considers parametric approaches and artificial intelligence based methods. The parametric approaches are mainly based on the relation between the load demand and the factors that affect it. The parameters are evaluated through mathematical models adopting statistical techniques on historical data of load and the affecting factors. The parametric methods can be divided in three main categories [18]:

- Time series prediction models,
- Regression models,
- Grey dynamic models.

2.1.2 Regression models to load forecasting

Regression models are based on the strong correlation between the load and its affecting factors, such as weather. This kind of method of mathematical modeling for global forecasting based on regression analysis was used to forecast load demand up to year 2000 [19]. Furthermore, Long-term forecast based on linear or linear-log regression models of six predetermined sectors has been developed [20]. The time series models are, for example, the Auto Regressive (AR), Moving Average (MA), and the Auto Regressive Moving

Average (ARMA) methods. Nowadays, these are popular and widely accepted by power utilities [21]-[23]. However, they require a huge amount of historical data in order to produce optimal models. Finally, grey system theory is successfully used to develop dynamic load forecasting models [24].

2.1.3 Artificial intelligence models to load forecasting

The artificial intelligence methods are further classified into Artificial Neural Networks (ANNs) based methods and Fuzzy Logic (FL) based methods. ANNs present some advantages for load forecasting, these are mainly due to their combination of both time series and regression approach. In fact, similarly to the time series, ANNs traces previous load patterns and predicts a load pattern using recent load data [17], [25]-[26]. Furthermore, ANNs are able to use weather information, perform nonlinear modelling and adaptation, without requiring assumptions on the relationship between load and weather parameters. Finally, Fuzzy Logic (FL) techniques allow uncertain or unclear data to be modeled. FL is able to cope with both numerical data and linguistic knowledge, despite the need of a thorough understanding of the fuzzy variables of the input and output relationships. In addition, a good selection of the fuzzy rules and membership functions that influence most of the solution of the application is required to adopt the FL approach [27].

2.2 Shipboard power systems load prediction techniques and approaches

In marine field, it is not available the same amount of information and measurements as it is in land microgrid applications, especially at the design stage where very little is known about the project ship. This is due to several factors. Firstly, almost every ship can be considered as a prototype due to several factors that characterize its main features (e.g. length, draft, beam, volume, speed etc.). Furthermore, in ship design there are many unknown characteristics, such as the power required by each user (e.g. which depends on the nature of the user, on the passengers behaviour, the weather conditions faced and so on). Moreover, the power required by the propulsive motors is one of the most relevant source of uncertainty in ship design (e.g. depending again on the places where the ship will operate, the weather conditions, the scheduled timetable of the ship and on the ship operative conditions).

In this context, it is evident that it is not possible, at least during the design phase, to apply the long-term forecasting methodologies listed for land applications, being them based on a large amount of available data and information about the past load demand. On the other hand, those methodologies become interesting and applicable in management phase, where data and measurements can be available thanks to the on-board automation system.

Other approaches and methodologies are available at the design phase of a shipboard power system. However, before introducing these methods to perform the EPLA, some useful definitions are proposed in order to in order to avoid misunderstanding.

2.2.1 Electric terms definition

There are several definitions for power and load operating in a power system depending on where the power is measured or calculated and which time interval is considered [28]-[33]:

- *Rated Power* is the value of nominal power delivered by the machinery at full rate. For those users whose nominal current value is known instead of power, this value must be converted to nominal power using an appropriate power factor (e.g. resistive loads usually provide a power factor of 1.0, loads from induction motors have a power factor value between 0.7 and 0.9, with higher values for those machines that are either bigger or newer).
- *Demand* can be defined as the load at the receiving terminals averaged over a specified interval of time and specific operative condition of the

ship. The time over which the load is averaged is the demand interval, determined depending on the particular application under exam.

- *Maximum Demand* is the greatest of all demands which have occurred during a specified period of time.
- *Diversity Demand* or *Coincidence Demand* is the demand of a combination of loads considered as a group over a specified time interval. The maximum diversified demand is often the value of most interest.
- *Non-Coincidence Demand* is the sum of the demands of a group of loads with no restrictions on the interval time to which each demand is applicable. It usually considers the maximum individuals demands.
- *Connected Load* is the rated power of a machinery in kW or kVA.
- *Peak Load* is the maximum power of a given load; it does not consider very short duration transients.
- *Operating Load* represents the power demand for a given ambient and operating condition of the ship, measured in kW. For the 24 hours average load calculations it corresponds to the average long-term load. Otherwise, for ship demand power calculation, the operating load represents should account also for the peak load and for the variance of the load around the average value for extended period. It is to be noted that it does not include the peak loads caused by the starting of large motors or the transient peak with very short duration.
- *Total Operating Load* is the sum of all the operating loads in a given ambient and operating condition for the ship.

There are also many factors, evaluated with a semi-deterministic approach, that are usually used to perform the EPLA:

- The *Diversity Factor* is the ratio between the sum of the individual maximum demands for the various subsystems to the maximum demand of the whole system under exam, as proposed in equation *(1)*. Being so defined, the diversity factor is equal or greater than the unity.

$$Kd = \frac{\sum max\ demand\ of\ each\ individual\ consumers}{Max\ concident\ total\ demand} \tag{1}$$

- The *Coincidence Factor* is the inverse of the diversity factor. It is defined as the ratio between the maximum coincident total demand of a group of consumers to the sum of the maximum power demands of each individual consumers, as reported in equation *(2)*.

$$Ks = \frac{Max\ concident\ total\ demand}{\sum max\ demand\ of\ each\ individual\ consumers} \tag{2}$$

- The *Demand Factor* is the ratio of the maximum demand of a system to the total connected load of the system. Can be defined as in equation *(3)*.

$$Ku = \frac{Max\ demand}{Total\ connected\ load} \tag{3}$$

- The *Load Factor* is the ratio of the average load over a specific period of time to the peak load occurring in that period, as proposed in equation *(4)*.

$$LF_{ij} = \frac{Average\ load}{Peak\ load\ registered} = \frac{1}{T_j \cdot P_{MAX_{ij}}} \int_0^T p_{ij}(\tau) d\tau \tag{4}$$

Where, LF_{ij} is the load factor for the i^{th} load considering the j^{th} ship operative condition, T_j is the reference time horizon for the j^{th} ship operative condition, $P_{MAX_{ij}}$ is the maximum power required by i^{th} load considering the j^{th} ship operative condition and $p_{ij}(\tau)$ is the instantaneous value of power required by the i^{th} user in the j^{th} ship operative scenario.

- The *Utilization Factor* is the ratio of the maximum power demanded by a consumer in a period to the rated power of the consumer, as reported in equation *(5)*.

$$UF = \frac{Consumer\ Maximum\ demand\ in\ the\ reference\ time}{Consumer\ Rated\ Power} \tag{5}$$

- There are three different types of *24 h average load calculations.* The first one is the *24 hours ship service endurance electric load*. This is the average anticipated ship service electric load expected over a 24 hours period for the ship service operating conditions (i.e. weather conditions and operative scenarios). This value includes both the safety margin and the service life allowance. The second value is the *24 hours ship service mission electric load profile*, which consists in the 24 hours period prediction of the electric load for the ship operating in the specified mission condition, for each possible ambient condition versus the speed in the specified ship speed-time profile. The last is the *24 hours ship service sustained electric load*. This is the average anticipated ship service electric load expected over a 24 hours period for the ship service operating condition corresponding to a cruising with self-defence capability (i.e. considering naval vessels) [28].
- The *Service Life Allowance* is a margin that accounts for an additional capacity incorporated into the power system to allow the future growth in loads due to modernizations of the ship and worsening of the electrical users and devices installed on board the ship [34], [35].
- *Ambient condition profile* consists of a different combinations of air temperature/relative humidity conditions and their associated percentage of time the ship will operate under those conditions. Unless specification, default ambient conditions profiles can be [28]-[36]:
    a) 25% of time at -12°C with 95% relative humidity
    b) 50% of time at 15°C with 95% relative humidity
    c) 25% of time at 38°C with 40% relative humidity.

2.2.2 Electric power load analysis approaches

The EPLA consists of a long-term prediction of the load peaks, without considering instantaneous power surge, which are caused by starting large motors or short duration peak loads. Otherwise, the 24-hour average load calculations consists in a long-term prediction of the average load. Most of the time, the shipyards adopt a combination of the previous approach in order to calculate the power demand.

This method consist in a long-term prediction of the average load considering margins for safety and service life allowance. In this perspective, it can be very straightforward but at the same time, inaccurate. These approaches are all shown in Figure 1 to allow comparison.

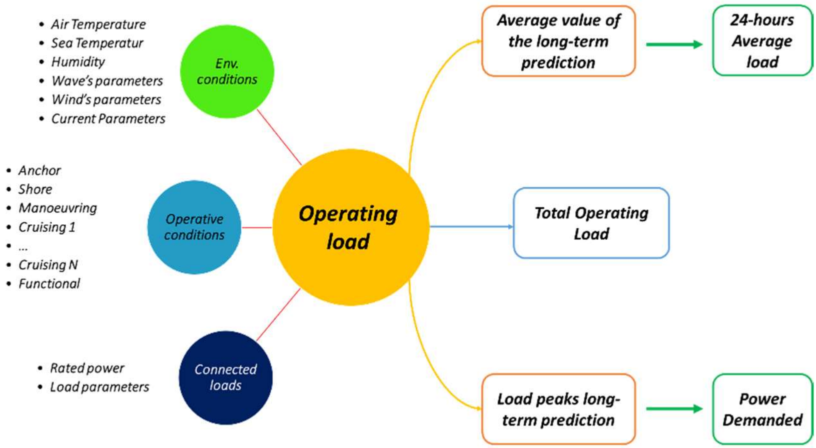


Figure 1 – Calculations performed during the EPLA

Designers usually assume a safety margin equal to 10% of the power demand, while the service life allowance is a margin that depends on the stage of the design. In fact, its value is higher in the first steps of the design and lower in the final steps. However, it can be usually considered equal to 30% for navy vessels [35].

Once the aim of the EPLA has been defined (e.g. among the calculation of the 24 hours average loads, the power demand and the total connected load), there several approaches available to perform it. The main approaches available can be classified as follow:

a) *Deterministic approaches*, which are based on factors that can be combined with the connected power of each user to calculate their operating load. These values are then joint together with a combining algorithm to evaluate the total operating load, the 24 hours average loads or the power demand, respectively depending on the factor adopted [4], [9], [28].

b) *Stochastic approaches* are based on the definition of Probability Density Functions (PDFs) and Cumulative Density functions (CDFs) for each random variables that affect the phenomenon (i.e. the power demand, the 24 hours average load or the total operating load). In this perspective, each load has to be stochastically characterized in order to identify which are the random variables that influence its behaviour [28], [34], [37].

c) *Modeling and simulation approaches*, which are based on the development of the physical model for the power system and perform simulations in different conditions based on that. This method is often used when specific loads are large compared to the power generation capacity. For this reason, they may require large amounts of rolling reserve, which is normally not reflected by the deterministic approaches. However, in modelling and simulation, a huge amount of data and information are required in order to develop the model and perform accurate simulations. As a result, in early stage of design, this method is not suitable. Furthermore, it is to be noted that, in every step of the design, this method results very time expensive and its results strongly depend on the precision of the model [28].

d) *Behavioural approaches* are based on the characterization of the behaviour of loads and their combination adopting stochastic process. Therefore, these methods propose a hybrid approach to load modelling that mixed together stochastic and deterministic models to provide the load prediction and its behaviour. This prediction also includes in-rush, reactive power and harmonic demand. An example is proposed in [39], where the model is applied to a naval vessel power system (i.e. to a DDG-51 class destroyers) taking advance of the actual data supplied by the Ships System Engineering Station (SSES) for the load modeling.

Each of the previous methods can be used to perform the EPLA, however, it is to be noted that each of them requires different information and provides a different reliability of the results. The main methods to perform the EPLA and their outcomes are reported in Figure 2 together with the main information usually required.

Traditionally, the most used method by the shipyards is the deterministic one [28]. For this reason, this method is explained below in more details in order to allow a better understanding.

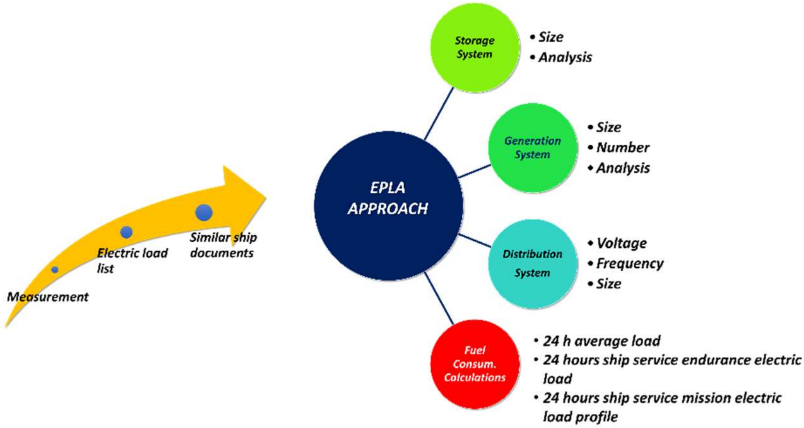


Figure 2 – EPLA's main inputs and outputs

2.2.3 Deterministic approach based on factors to perform the EPLA

The deterministic approach is the most used by shipyards being extremely straightforward and simple to apply. In addition, it should be noted that it requires few information that may be available, albeit at different levels of detail, at each stage of the of the ship design. Being based on the use of factors that has been calculated on dated ships, it fails to take satisfactory account of the new power systems installed on board.

One of the main assumption of this method is the knowledge of the principal electric users feature. The so-called Electric Load List (ELL) reports these characteristics as input to the EPLA.

This list reports information such as the number of machineries installed for each user (e.g. number of pumps for the fresh water-cooling pump system), the rated power of each machinery, the working efficiency, the number of poles, the voltage level and so on. In the ELL, loads are usually divided according to their service, adopting for example the Ship Work Breakdown Structure (SWBS).

The SWBS divides all the users in the following categories [40]:

- the numeration *200 - 299* reports the loads that serve the propulsive power system of the ship
- *300 - 399* listens the loads that serve the electric system (e.g. the lighting system)
- then, *400 - 499* proposes the loads that attend the command and surveillance systems
- moreover, the numeration *500 - 599* reports the auxiliaries users (i.e. not belonging to the propulsion system) such as the Heat Ventilation and Air Conditioning (HVAC) system
- further, *600 - 699* proposes the load belonging to the general outfitting and furnishing (i.e. here the most important loads are those regarding the galley service)
- finally, only for naval vessels, the numeration *700 - 799* reports the loads related to the weapon system.

Once the electric users have been identified and divided, it is required to know the main ship operative conditions and the corresponding behaviour of the users in these conditions.

Traditional conditions that are common for every ship are:

- *anchor condition*, is the operating condition where the ship is stationary and supplies all the power demand by itself
- *shore condition*, when the ship is in port and all the power demand is supplied by the on-shore grid
- *cruising condition*, is a ship operating condition corresponding to the ship cruising at its design speed, the power demand is supplied by the on-board power system

- *functional condition*, when the ship is performing its design function (e.g. dynamic positioning for a supply vessel, loading/unloading for a bulk carrier or container ship and battle for a naval vessel)
- *emergency condition* is a ship operating condition in which the ship's power demand is supplied by the emergency generator with all the service generators down.

Other traditional source of information, also reported in Figure 2, are documents from similar ships. These documents can be, for example the instruction to the commander (i.e. reporting useful information on the ship operating condition and best practices), a complete ELL, machinery reports (i.e. useful to calculate the factors or perform fuel consumption calculation), etc.

However, there are further source of information that are more difficult to be obtained in design phase, both from similar and twin ships. These are for example field measurements of the power absorbed by the users, the active and reactive power supplied by the generation system, the ship operating conditions and the weather conditions faced by the ship.

If measurements were available, it would be possible to update the factors used to perform the EPLA in order to find results that are more accurate. When these data are available, the conditions affecting the choice of load factors and the methods used to determine them include:

- in selecting, for example, the size of a motor that drives an auxiliary device at its rated output, usually a larger motor than actually needed is chosen, due to some margin in excess or the choice of standard motor frame size,
- if some equipment operate continuously at a steady load in a specific ship operate condition, the load factor (i.e. the most used factor to perform the EPLA) for those equipment may be calculate as the ratio of the operating load to the connected load of the equipment. On the other hand, if the load is intermittent or cyclic, the factor shall be evaluated based on the aim of the prediction. For 24-hours average load calculation used in endurance, annual and monthly fuel calculation. In this way, the load

factor is set equal to the ratio of the long-term average load to the connected load of the equipment (e.g. as shown in Figure 1). Otherwise, for the demand power calculations, the load factor can be approximated applying the curve shown in Figure 3.

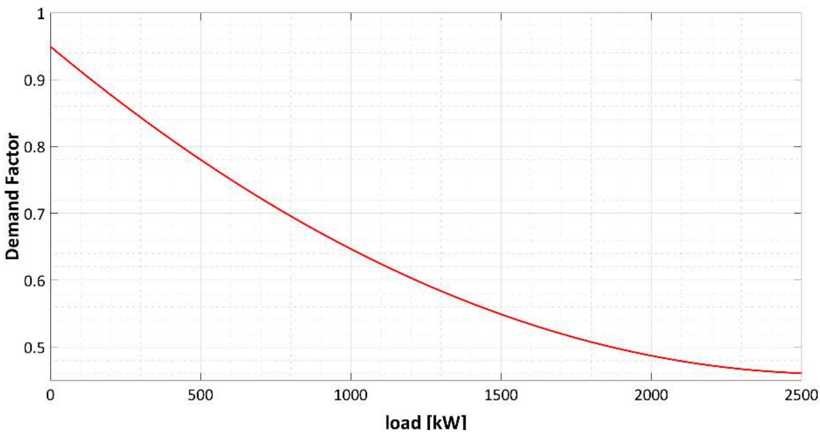


Figure 3 - Demand factor function of the connected load

The typical procedure in use at the shipyards to perform the EPLA is here reported and explained. As it is possible to note this is based on the use of Load Factors (LFs) as they have been previously defined. The main steps of this procedure are:

- loads subdivision depending on the SWBS nomenclature,
- identify the number of users for each electric load,
- detect the connected power for each user,
- evaluation and set of the efficiency of each device,
- calculate the power absorbed to the grid by each load,
- identify the main ship operative conditions of interest,
- identification, calculation and assignment of the correct load factor to each load,
- identify the number of users switched on in each ship operative condition for each load,
- calculate the operating load in each scenario,

- consider the efficiency of transformers to identify the power required to main bus or buses,
- calculate the power required for the propulsion in cruising and manoeuvring conditions (e.g. only for ships with an electric propulsion system),
- Margin and service life allowance application to the total operating load,
- Evaluation of the total power demand in each scenario and identification of the maximum power demand (e.g. to select the total power to install for the generation system).

As it is possible to note, the algorithm to calculate the power demand and perform the EPLA is very simple and straightforward. However, it does not represent a long-term prediction of the peaks.

Afterwards, once the power demand in the different ship operative conditions is known, it may be possible to select the size of the generation power system and the number of required diesel generators.

2.3 Approaches to power generation system sizing for ships

In order to properly select the power generation system size it is required to know the power demand in each ship operative condition. In fact, the generation system must guarantee enough power to meet the peaks during the ship life. In this perspective, the load prediction should be a long-term forecast of the peaks.

Traditionally, the minimum value of power to be installed into the power generation system on board ship is evaluated considering the maximum power demand.

Once this minimum value has been identified, other aspects shall be considered in order to properly select the number of diesel generators and their sizes (e.g. for merchant ships) [40]:

- in design phase, each diesel generator should not be loaded for more than the 90% of its rated power (i.e. to guarantee both a reserve of power in case of extreme conditions and to preserve the generators from their critical working load)
- the main source of electrical power shall consist of at least two generating sets
- the number of diesel generators and their sizes must be such to guarantee enough power to the minimum comfortable conditions and supply those services necessary to provide normal operational conditions of propulsion and safety in case of loss of the biggest generator
- in addition, the generating sets shall be such to ensure in case of loss of any generator, the reaming sets shall be capable to provide the electrical services necessary to start the main propulsion plant from dead ship condition (e.g. black start)
- the number of diesel generators depends also on the amount of power installed. In fact, if the power installed for the generation system exceed 3 MW, the main busbar shall be divided into at least two main busbars.

Typically, being the result of the deterministic EPLA merely a number, these normative are satisfied adding margins and oversizing the power generation system such as all the on board power system as well. This results in poor performances, lower efficiency, high management and installation costs of the system as well as high polluting emissions.

3 Probabilistic Approach to Shipboard Electrical Power Load Analysis

Nowadays, an increase in the total electric power installed on board ships is revealed, also thanks to the recent developments on power electronic devices. Moreover, the recent introduction of renewable resources in terrestrial electrical applications has led to the concept of microgrids. In addition to this, the parallel development of the digital communication system technologies allows to talk about *smartgrid*[2], regarding those microgrids that adopt advanced automation and communication systems based on the *"smart technologies"*. In this context, the traditional approaches to EPLA for shipboard power systems have become less effective to predict accurately the total operating load of the system. In fact, these methods were reliable and accurate when applied to old ships, where the on board power system was not as significant as for the recent ships. The probabilistic method

[2] *In short, the digital technology that allows for two-way communication between the utility and its customers, and the sensing along the transmission lines is what makes the grid smart. Like the Internet, the Smart Grid will consist of controls, computers, automation, and new technologies and equipment working together, but in this case, these technologies will work with the electrical grid to respond digitally to our quickly changing electric demand [41].*

that is here presented allows the designers to adopt approaches based either on experimental readings or on the traditional inputs to EPLA (e.g. knowledge of the designers, manufacturers and documents from similar ships). The results yielded applying this methodology to two case studies (i.e. a bulk carrier and a large cruise vessel) show the real possibility to perform a more accurate and detailed prediction of the total operating load. Finally, a possible reduction of the total amount of power installed for the power generation is also pointed out.

This chapter has been developed based on the following ideas. Firstly, in order to introduce the main topic of this chapter, a *literature review* on load prediction techniques adopted in marine is here presented, with a special focus on the probabilistic approaches to load prediction. Therefore, the *main hypotheses* of the probabilistic method developed in this thesis are formulated. One of the most critical and central issue in the probabilistic approach to EPLA is the probabilistic characterization of the loads. This means that for each user, the random variables that describe its operating load, should be identified. Moreover, probability distribution functions have to be selected for each random variable. In this chapter, three *modeling approaches* are formulated in order to identify the random variables for each user and, additionally, four methods are proposed to identify the corresponding probability distribution functions, depending on the input information and the phase of the design. Each method has been tested and compared to each other. Those depending on experimental readings adopt field measurements performed on board a naval vessel, which due to confidentiality reasons can not be specified. A *Monte Carlo Simulation* process is adopted in this formulation in order to combine the loads and evaluate the total operating load.

Furthermore, a *sensitivity analysis* on the load characterization has been performed and the probabilistic approach applied to two *case studies* to validate the formulation. Finally, some *conclusions* and considerations are drawn.

3.1 Context

In recent years, we have seen a growing interest in ship energy efficiency performances, addressed both during the ship design process and at ship management level. This is due to several factors among which the economic aspects (actually influenced by the fuel price, more or less convenient depending on periods) and much more important the normative context in the maritime field [28], [42]. In fact, the growing interest in global environmental issues has led to increase IMO (International Maritime Organization) activity in providing some regulations to this aim. These rules provide a more efficient management of ships that are already operating, with the introduction of the SEEMP (Ship Energy Efficiency Manage Plan). On the other hand, for new buildings, a design index, the EEDI (Energy Efficiency Design Index) is requested. This is focused on a significant reduction in GHG emissions (GreenHouse Gas), obtainable with a reduction of the power installed on board or with the use of more efficient engines, compared to those used in the past. Ship design is a very complicated engineering process, although it is a rather well-defined procedure, applied to possibly very different *"final products"* ship typologies. In recent decades, we have witnessed a considerable increase of electrical components on-board. This increase, which was enhanced by "Power Electronics" development, has the aim to improve the flexibility, the efficiency and reliability of the on-board systems. Whereby, the ever-increasing demand for safety, reliability, operational economy and environmental efficiency are the driving forces for increasing the use of the electrical power on board of different types of vessels. As mentioned previously, ship design is a complex and articulated engineering process, which requires several phases. Within this process fits the EPLA (Electrical Plan Load Analysis). It consists in the evaluation of the electrical power peak demand in different ship operational scenarios (e.g. cruising, manoeuvring in port, operation and emergency scenarios are typical). The power required to generators is traditionally evaluated using specific coefficients (e.g. Load Factors), which might have different values for each load type installed on board and scenario under analysis. The sum of the previous results provides the value of the maximum power demand to the generators. After this phase, it is possible to proceed with generators sizing, study possible energy storage solutions, perform fuel consumption evaluation, moreover, perform economic assessments on the system cost, both in the short and long term. In this chapter, new methodologies based on probabilistic characterization of the loads and statistical simulation will be introduced, explained and applied to case studies in order to validate them.

3.1.1 Introduction to the deterministic approach to EPLA

To allow a comparison between the traditional deterministic approach to EPLA and the probabilistic approach that is proposed in this chapter, the former is here briefly described. The main assumption for the deterministic approach is the use of deterministic factors (i.e. those defined and explained in paragraph *2.2*) to calculate the operating load of the electric users. The main steps of a traditional EPLA based on deterministic factors are proposed in Figure 4.

Figure 4 - Deterministic approach to EPLA

These are the identification of the main inputs regarding information on the electric users, the deterministic calculations to evaluate the operating load and the results evaluation. The operating loads for these users are calculated multiplying these deterministic factors by the rated powers reported in the electric load list, as proposed in equation *(6)*.

$$P_{ol_{ij}} = n_{ij} \cdot f_{ij} \cdot P_{rated_i} \tag{6}$$

Where, n_{ij} is the number of devices in function, f_{ij} is the deterministic factors of the i^{th} load at the j^{th} operative condition of the ship, respectively. Moreover, P_{rated_i} is the rated power of the i^{th} load and, finally, $P_{ol_{ij}}$ is the operating load of the i^{th} load at the j^{th} operative condition. The total operating load (P_{Tot_j}) in each ship operative condition is then calculated as proposed in *(7)*.

$$P_{Tot_j} = \sum_{i=1}^{N} P_{ol_{ij}} \tag{7}$$

The total power required to the generation system is identified considering the maximum total operating load calculated in *(7)*. In addition, it should be noted that the total operating load must be covered by the generation system also in the case of fault of one generator. A briefly example of the deterministic EPLA is proposed in Table 1.

TABLE 1 - DETERMINISTIC EPLA CALCULATION STEPS

Load Name	P_{rated_i}	**Shore**			**Manoeuvring**			**Cruising**		
	[kW]	n_{ij}	f_{ij}	$P_{ol_{ij}}$	n_{ij}	f_{ij}	$P_{ol_{ij}}$	n_{ij}	f_{ij}	$P_{ol_{ij}}$
HT FW cooling pump	9.4	1	0.9	8.5	1	0.9	8.5	0	0	0
Preheating pump ME	1.7	0	0	0	0	0	0	1	0.9	1.5
ME chem. cleaning water pump	2.4	0	0	0	0	0	0	1	0.9	2.2
Fuel oil supply pump	1.9	1	0.9	1.7	1	0.9	1.7	1	0.9	1.7
Fuel oil circulating pump	3.9	1	0.9	3.5	1	0.9	3.5	1	0.9	3.5
Total operating load [kW]	P_{Tot_j}	**13.7**			**13.7**			**8.9**		

3.2 Literature review

The design of an energy system primary involves a phase where the equipment must be sized. Considering a general power system, the most important characteristic of the electrical equipment is the power absorbed to provide their function. Therefore, the sizing phase is traditionally based on a calculation that preliminary estimates the loads.

Nowadays, in terrestrial transmission and distribution systems the aim is primarily to forecast the power absorbed by the users in order to plan for the commissioning of power stations [43]. These long-term forecasting tools have already been introduced in *2.1*. For electric distribution systems of either the industrial and tertiary type, power demand forecasting is performed adopting a power report [44]. Although standardized, this report becomes increasingly difficult to determine due to the recent increasing number of electric users that allow the use of power converters.

On-board power systems are often treated as industrial systems, as their characteristics and uses are often closer to this type than to those shown by transmission or terrestrial distribution networks. In other words, as already stated, a shipboard power system can be identified as a microgrid. Thus, the rules used to perform a power report seem unsuitable in this particular case. In this context, as often happens in design phase, the system designer will naturally tend to increase safety margins leading to an over-sizing of the system. Consequently, repercussions on the investment, production and management costs are pointed out.

To overcome this conditions and the traditional power report approach (here also named as *"deterministic electrical power load analysis"*), in [45] a probabilistic model for residential load is proposed. In this work, the load uncertainty is modeled applying a Beta distribution and, by separating the probabilistic load uncertainty and the load parameter uncertainty (i.e. modeled applying a bivariate distribution), the model becomes useful. This method has been tested using a Monte Carlo simulation for practical design purpose.

In [28], Doerry has proposed several approaches to perform the EPLA for surface vessels. Among these methods (e.g. deterministic, probabilistic, simulative and zonal), a probabilistic approach to EPLA is introduced.

Moreover, in [46] a probabilistic method to take into account the uncertainties of loads and wind production in unbalances distribution systems is proposed. This method is based on Monte Carlo simulation applied to the non-linear three phase load flow equations, including wind farms, thereby taking into account all load and line unbalances, which can characterise the distribution systems. Consequently, the method allows the evaluation of phase-voltage and unbalance factor probability.

In [47], a stochastic approach that considers electrical quantities as random variables has been successfully applied to the analysis of the generation and propagation of the harmonics in the electrical systems with low short-circuit power.

In [48], Robinson presents a method based on a systems engineering approach, applying a probabilistic analysis of electrical loads at each transformer, based on the EPLA, in order to incorporate risk mitigation into radial or zonal electrical system, to verify adequacy and reduce cost of transformers, on-board a navy vessel.

This chapter, on the other hand, presents a method based on the probabilistic characterization of each electric user present on-board ships, in order to predict the total operating load, the power demanded to the power generation system and, consequently, allow designers to efficiently design and size the generation.

3.3 Hypothesis of the method proposed

The power demand in both land and shipboard grids depends on several parameters. Many of these present uncertainties that are intrinsic to their random nature. For example, even in land-based applications, with the introduction of renewable and uncontrollable energy sources, the available power has also become a source of uncertainty. Therefore, it must be predicted for the stability of certain power grids [49].

On the other hand, in marine applications uncertainties are due to propulsion power, which strongly depends on the sea state, the heat ventilation and air conditioning (HVAC) load, which is a function of temperature and humidity, human behaviour and, in a more general perspective, depending on the ship management. Therefore, a probabilistic modeling of exogenous variables may be useful to guarantee a greater precision and reliability in describing the behaviour of power demand on board the ship.

This chapter presents probabilistic modeling for the electric loads, based on statistical analysis of consumption [50]. Load's modeling is discussed in both a theoretical and practical perspective [51].

The power consumed in a distribution network at each moment, whether it is a terrestrial or a shipboard application, is the result of many phenomena, where several variables and parameters are involved in a more or less dependent manner. If these parameters are changed by chance, it is then possible to formulate the hypothesis according to which, these powers are result of random phenomena [37].

Being the power absorbed by the electric users the result of partially random phenomena; a probabilistic approach considers the electrical quantities (e.g. power or current) as random variables. Therefore, the loads variable operating regime (e.g. different values of the power absorbed or operating load) of the loads and the different diversity effects (e.g. contemporaneity between loads and their utilization time horizon) that can occur on the power system are likely to be characterized and governed by probability laws. Thus, the aim of the probabilistic approach is to identify firstly the general behaviour of the devices, with the purpose of providing a more efficient and accurate estimation of the total operating load.

Differently from what happens in the deterministic approach to EPLA, in the probabilistic one, being the load power considered as a random variable, this is no longer represented by a single deterministic value (e.g. obtained from deterministic factors such as the load or diversity ones), but through statistical laws.

In this context, the probability density function (PDF) indicates the dispersion of the quantity and the cumulative distribution function (CDF) indicates the probability of not exceeding a given value, as proposed in Figure 5 and Figure 6, respectively.

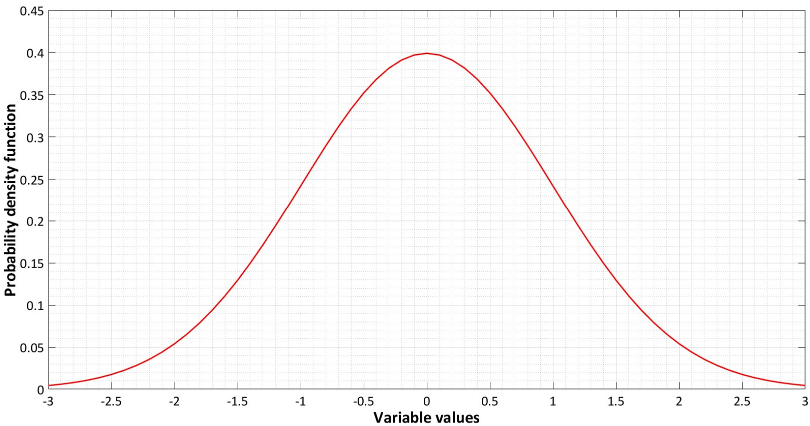


Figure 5 - Normal probability density function for a random variable

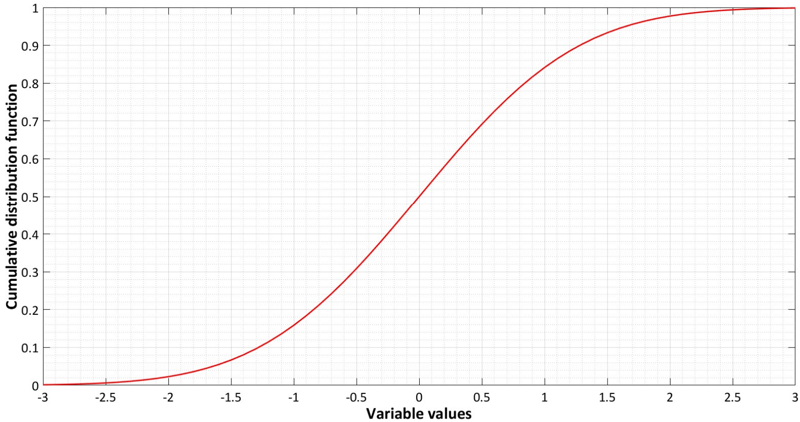


Figure 6 - Normal cumulative distribution function for a random variable

In this perspective, the aim of the EPLA is not focused to obtain one single value identifying the load power, but the probability density function $f_{p_{load}}$ describing the behaviour of the random variables that characterize the load power. Therefore, the problem is to determine the values p_{load} as proposed in equation *(8)*. Where, P_{laod} are the possible operating load values assumed by the random variable p_{load}.

$$\mathrm{P}[p_{load} \leq P_{load}] = \int_{-\infty}^{P_{load}} f_{p_{load}}(p_{load}) \cdot dp_{load} \qquad (8)$$

As it happens in the deterministic EPLA, where the total operating load is equal to the sum of all the operating loads, also in the probabilistic approach to EPLA the total operating load PDF and CDF are calculated as the sum of all the random variables describing the operating loads of all the electric users installed on board.

The problem raised by the sum of random variables is standard in probability theory [51]-[53]. However, this problem can be extremely complex in this context. To simplify it, some assumptions *"a priori"* must be stated and identified together with proprieties of the variables and their probability law.

The thorny issue of the choice of safety margins, both on the individual loads (e.g. through the selection of the coefficients values) and on the total operating load value can be overcome in this methodology, being the nature of the PDFs and CDFs intrinsically probabilistic (e.g. accounting for the uncertainties). In fact, these intrinsically take into account the uncertainties related to the operating load of each single user and, furthermore, those related to the total operating load, providing in addition information about the probability of occurrence of extreme values (e.g. not available, on the other hand, applying the deterministic approach to EPLA).

In this way, it is possible to size the system components on both a risk assessments and long-term forecast basis; rather than adopting the traditional approach to sizing, which is based on a single value of power required with the supplement of a safety margin.

A further significant hypothesis of the probabilistic methodology is that some loads may present a behaviour that depends on the system configuration. In fact, there are loads, which behaviour is related to the environmental conditions, the ship operating conditions, the presence or absence of other loads in operation or on the level of power absorbed. This, as it will be explained hereafter in details, involves conditional probabilities and correlations between random variables.

3.4 Algorithm for the probabilistic electrical power load analysis

Once the main hypothesis needed to develop a probabilistic approach to EPLA have been stated it is now possible to formulate the algorithm to the probabilistic EPLA. In this perspective, the main steps of this algorithm are:

- the load subdivision in logical classes depending on their function, behaviour or on the system they serve, for example adopting the work breakdown sequence (WBS) approach,

- the identification of the number of users installed for each load (e.g. the chilled unit pumps can be composed of 4 pumps),
- the selection and statement of the main ship operative conditions considered for the EPLA (e.g. at least anchor, manoeuvring, cruising, function and emergency are often considered),
- when measurements on the power absorbed by the electric users on board similar ships are available, this dataset must be analysed in order to obtain important information on the user's behaviour,
- considering the information available, a load characterization of each electric user considered it is required in order to identify the random variables that describe the power absorbed by each load,
- once the random variable have been identified, accordingly to the information available, it is possible to perform a statistical characterization. This consists in assigning a proper distribution density function to describe the behaviour of each random variable (e.g. the method applied can vary depending on the information available, as proposed in paragraph *3.6*),
- in the case that dependencies and conditioning exist between the random variables, it is require to eliminated their conditions in order to perform a statistical simulation,
- the statistical simulation is performed (e.g. adopting a Monte Carlo or a Point Estimated Method approach),
- the total operating load probability and cumulative distribution functions are calculated for each ship operative scenario considered,
- the total operating load un-conditioned to the probability of each scenario should be evaluated,
- the total power demanded by the loads is calculated as the long-term peak forecast of the total operating load (unconditioned),
- in case of a ship with an electric propulsion system, the power required by this system have to be evaluated and statistically characterized,
- it is possible to perform risk assessment, long term forecasting and fuel oil consumption calculation,
- finally, it is possible to select and size the power generation system.

These main steps are briefly summarized in Figure 7.

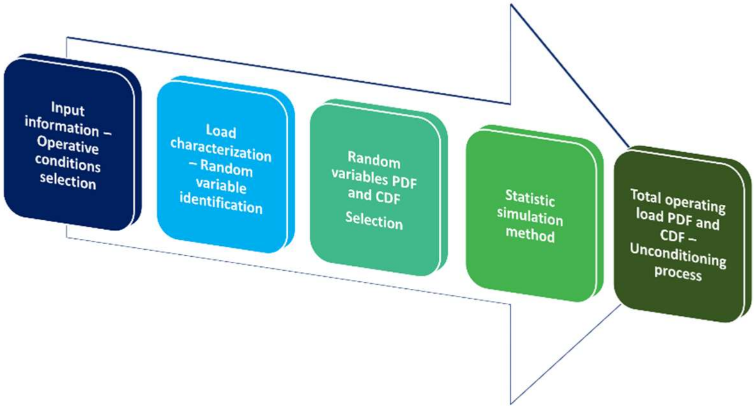


Figure 7 - Main steps of the probabilistic EPLA

These steps will be explained in detail in the following paragraphs. In some cases, several approach will be introduced to perform the same task, depending on the available information or the design phase considered.

3.5 Load characterization

The proposed approach is actually based on the probabilistic modeling of loads. Therefore, the main variables describing the power drawn by the loads of the power system should be modeled in a probabilistic perspective. Whereupon, the random variables that can describe each load model are identified and PDFs selected in order to describe them. These PDFs can be selected according to the design knowledge or based on measurements from similar ships. In this second case, several approaches are available to perform such selection.

The methods to discriminate distributions depending on the available measurement are, for example, the Pearson's chart method (e.g. skewness and kurtosis chart) and the goodness of fit tests, which employing mathematical test to select the best distribution to a population of sets. Moreover, artificial neural networks (ANN) can also be applied to this task adopting, for example, a feed-forward neural network to discriminate between distributions (e.g. as a goodness of fit test).

Finally, in this paragraph, methods and types of dependences and correlations between variables are presented. As proposed in literature [28], usually, three types of load are distinguished in particular and are here described.

3.5.1 Constant loads

First load model is the constant one. In this model, an i^{th} device p_i absorbing power P_k can be represented by the probability law reported in equation *(9)*.

$$\mathrm{P}\left[p_i = P_k \right] = 1 \tag{9}$$

In fact, in this model, the device has only one mode of operation when it is in function. For example, this can be the case of the resistive loads [54].

3.5.2 Loads with operative states

Secondly, a device whose power takes several finite specific values, can be characterized by several probabilities. In a ship, for example, this is the case of radar system, which presents different operating modes with constant values. A typical radar has three or more modes and corresponding power levels. Assuming three operating states (e.g. E_1, E_2 and E_3) with three corresponding power levels (e.g. P_1, P_2 and P_3), the model can be defined as in equation *(10)*.

$$\begin{gathered} \mathrm{P}[\, p = P_1 \,] = m \\ \mathrm{P}[\, p = P_2 \,] = n \\ \mathrm{P}[\, p = P_3 \,] = q \end{gathered} \tag{10}$$

Where m, n and q represent the respective probabilities according to which the load is in the state E_1, E_2, E_3, respectively. These are positive quantities and their sum is equal to 1.

Loads that can be described with such a model are those depending on the system configuration. This means that, depending on the operative conditions or other factors, these loads assumes a configuration instead of another one (e.g. a radar system in a naval vessel assume different operating profile depending on if the unit is *"in combat mode"* or not).

3.5.3 Continuous variable loads

Finally, there are loads that continuously vary the power absorbed over time. These can be modeled by a probability density function $f_{p_{load}}$, defined in equation *(8)* and describing the dispersion of the power values.

It is to be noted that also a description in "current perspective" would be possible, instead of the "power perspective" one. However, modeling the current amplitude is not always sufficient. In fact, in an AC power system, information on the amplitude i and the phase φ are necessary. Therefore, the current absorbed by a load must be governed by a pair of random variables $\{i,\ \varphi\}$ characterized by a joint probability density function $f_{I\Phi}(i,\varphi)$, as proposed in equation *(11)*.

$$\mathrm{P}[\, i \leq I\,] = \int_{-\infty}^{I}\int_{-\infty}^{\Phi} f_{I\Phi}(i,\varphi)\,did\varphi \qquad (11)$$

However, such approach (i.e. in current perspective) to load modeling can be very difficult and time expensive. Therefore, in the proposed method, a model in *"power perspective"* has been preferred (i.e. active power).

Afterwards, it is to be noted that, according to the data available in each design phase of the shipboard power system, a models can be based on [37]:

- a description of the operating modes and the corresponding load powers, detailed by a specification. These information require a translation in terms of statistic parameters and laws related to the powers;
- periodically experimental readings, over a specified time frame, taken directly on a certain load or on another one that presents the same

function with a similar mode of operation (e.g. this is the case of data collected on similar ships).

3.5.4 Variables identification

The identification of the random variables is a critical and important phase of the probabilistic approach. In fact, once the model that best suits each electric load on board has been identified, the identification of the random variables defines which aspects influence the value of operating load.

In a simplified model, at least two random variables should be defined. The first one identifies the amount of power absorbed by a load, when this is online. The second one, on the other hand, account for the percentage of time this load is online in a reference time horizon.

In this perspective, it is possible to note that, these variables are the statistical translation of deterministic concepts such as the load factor (i.e. power absorbed compared to the rated one) and the utilization factor (i.e. time a load is online in a reference time horizon), traditionally adopted by shipyards. However, this does not mean that the probabilistic approach depends on the deterministic one but, rather, that the basic aspects that describe the operating load are the same (e.g. operating time and power absorbed).

Further aspect that can be adopt and identified as a random variable is the air temperature. This one, combined with the humidity, are useful information to describe the operating load of heat ventilation and air conditioning (HVAC) system, which is one of the most power users on-board a ship. In fact, the load behaviour of this system is strongly dependent on these variables.

The law supplied by the ISO 7547 to describe the dependence of heat transmission losses and gains (Φ) to the air temperature (e.g. that directly influences also the power absorbed by the HVAC system) is proposed in equation *(12)*.

$$\Phi = \Delta T \cdot [(k_V A_V) + (k_G A_{VG})] \tag{12}$$

Where, ΔT is the difference in air temperature between air-conditioned and non-air conditioned internal spaces, expressed in kelvin. k_V is the total heat transfer coefficient for the surface A_V. This is the area excluding the side scuttles and rectangular windows. On the other hand, k_G is the total heat transfer coefficient for surface A_G, where A_G is the area of the side scuttles and rectangular windows.

From equation *(12)*, a linear dependency between heat transmission and temperature can be generated. In the same way to the HVAC system with the air temperature, the central cooling system shows a strong dependency with the sea temperature and the power delivered by the main engine (e.g. in case of a ship with mechanical propulsion system) and generators [55]. The operating load is directly dependent on the heat exchanged. Moreover, the heat exchanged (Q) is proportional to the water mass flowing (m_{water}) into the piping, the specific heat for the sea/fresh water (c_p) and the water temperature (ΔT) in and out of the system, as proposed in equation *(13)*.

$$Q = c_p \cdot m_{water} \cdot \Delta T \tag{13}$$

Finally, there are devices with a behaviour dependent on the configuration of the system. These loads, depend on the operative condition of the ship (e.g. as already reported this is the case of the radar system) or on the state of others (e.g. this is the case of several pumps, which are online only if a specific system is online itself, or they absorbs a specific power which is proportional to that absorbed by another user).

In Figure 8, an example of load depending on the configuration of other loads is reported.

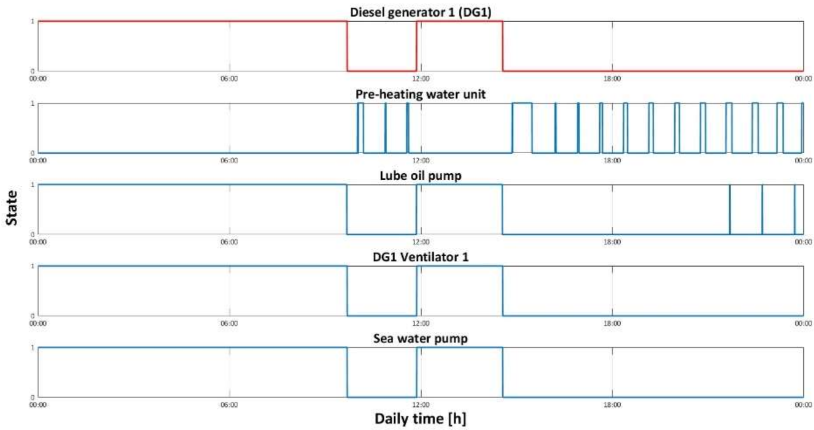


Figure 8 – Correlations between diesel generator and some auxiliaries

In the case of the HVAC system or the central cooling one, it is required to set the temperature as a random variable (e.g. air or water depending on the system) in the same way of the power absorbed and state ones. Therefore, such system may be described with three random variables. It is evident that conditional probabilities are involved in this case.

In the case of systems such as pumps or compressors, these often depend on the state of other user; therefore, a dependency to this user should be imposed. Users that regulate the operational behaviour of others are here named as *"masters"*. On the other hand, those users that depend on others are named *"slaves"*. An example of this model is proposed in Figure 8, where the master load (e.g. in red) is the diesel generator 1 and the others are the slave ones (e.g. in blue).

In Figure 9 a typical relation between masters and slaves is proposed. These relations between masters and slaves are presented in the following sections in more details. In Table 2, a brief summary on the possible models describing the behaviour of a device and the related variables is proposed.

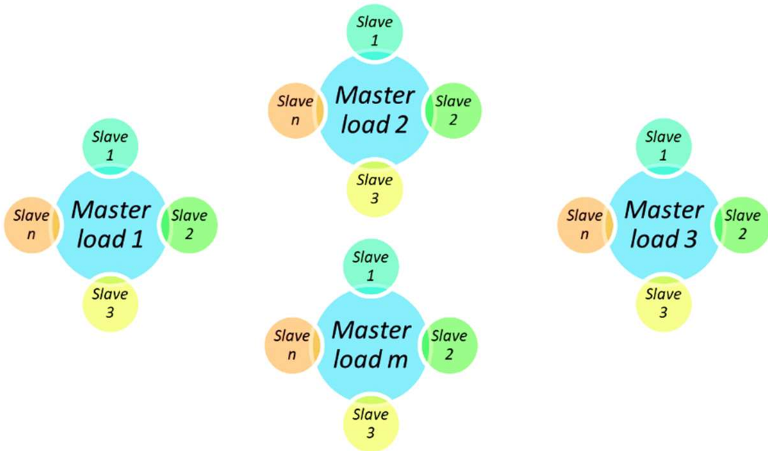


Figure 9 - Masters and slaves loads relation

TABLE 2 –MODELS AND VARIABLES DESCRIBING ELETRIC USERS

Model	Random variable	Example
Constant load	State (on/off) Power absorbed	Lighting system Resistive loads
Load with states	State (on/off) Power absorbed Dependency to the configuration Exogenous variables	Radar and Communication system
Continuous variable load	State (on/off) Power absorbed Dependency to the configuration Exogenous variables	Pumps, compressors, electric engines, etc…

However, it is to be highlighted that also constant load can be subject to the configuration of the system or to the ship operating condition. This is the case of the navigation lighting system. In fact, depending on the type of ship and on the scenario in which it is operating, this lighting system can be on or off and present a different number of lights on. It can also be possible to model this load such as a "load with states", where the different states depend on the configuration, as proposed in Figure 10. Therefore, as shown in Figure 10, the lighting system, if considered as a group of users, presents a multi states behaviour. The different states in the power absorbed are mainly due to the different number of light bulbs switched on and not on different level of power absorbed by the single light bulbs.

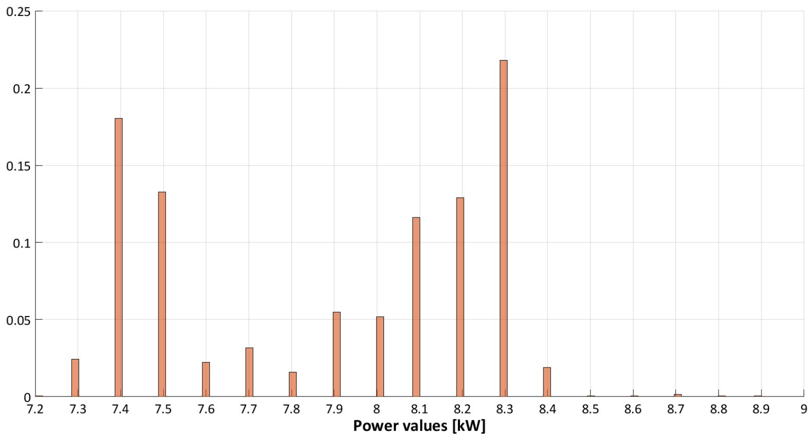


Figure 10 – Loading states for lighting system

In this context, it is possible to state that different models can be applied to each load and the choice depend only on the available information and on the detailed required. Therefore, in the first phases of ship design, where very little is known about the ship characteristics or the users installed, a simplified approach can be applied; where, system such as lighting or HVAC are modeled as a group of users and two variables (e.g. state and power absorbed) are selected.

In further phases of the ship design, when more information are available about the system and the users installed, a more detailed model can be applied. Such a model can considers single device, instead of a whole group of users, and apply more than two variables in order to describe the user behaviour.

Finally, when sufficient knowledge about the system is available, also dependency and configurations can be accounted into the model.

3.6 Statistical characterization of random variables

Hence, once the load characterization that was presented in the previous paragraph has been applied to the electric users of a power system (e.g. a shipboard power system), the models and the random variables that describe their behaviours are identified. To model correctly these random variables, a statistical translation of their actual behaviour is required. Therefore, the probability density functions that best describe the dispersion of the random variables values should be identified. This selection can be performed adopting three different approaches:

a. the first one, which seems to be suitable in the early stages of the design, is *"modeling using a specification"*. The design of an energy chain or a network is based on specifications describing the consumers that will be connected to it [37]. Information should be sufficient to establish a probabilistic model of these consumers. This enables their statistical translation. These information can be obtained from manufacturers, manuals, literature or similar systems.
b. A second approach, is *"modeling using deterministic factors"*. This approach adopts the deterministic factors as input information to formulate probabilistic models of the random variables identified. In this perspective, load factors (see paragraph *2.2.1*) can describe the amount of power absorbed by a consumer when this is online. On the other hand,

the utilization factor (see paragraph *2.2.1*) can describe the probability of this consumer to be on in a reference time horizon.

c. Finally, the third one is *"modeling using experimental readings"*. This approach is the most detailed one and allows an accurate and detailed description of consumers' behaviour. Therefore, in order to obtain these load models, experimental readings are adopted.

Statistical indexes such as the average and standard deviation are determined using these recorded data. To convert the measurements into histograms, the *Sturge's empirical rule* is a good compromise by defining a reasonable number of classes [57] in which the data are divided in order to show the occurrence frequency of each classes.

In fact, in this perspective, this method adjust the number of classes (i.e. bins) depending on the number of observations, as proposed in equation *(14)*.

$$N_{class}=1+\frac{10}{3}\log_2 N \tag{14}$$

However, compared with the Scott or the Terrel-Scott (TS) rules, the Sturges' one may have too few bins when large samples are adopted, as proposed in Figure 11 for a sample sized 10^6 observations.

The Scott rule is reported in equation *(15)*. The bin width is equal to $3.5\sigma n^{-1/3}$ for a normal PDF. However, the cumulative frequency distribution or the frequency histogram can also be approached or identified by a known distribution function. It is to be noted that, being not possible to have endless observations for a measurement, applying a continuous distributions to a sample is an approximation. In fact, measurements are discrete for their nature. The greater is the number of observations for a measurement, the more a continuous distribution can fit the sample. This is shown in Figure 12, where a continuous distribution has been applied to the sample proposed in Figure 10 and Figure 13. In this context, the random variable identifying the power absorbed (i.e. conditioned to the number of lights on) by this system is *"strongly discrete"*; although, the continuous distribution adopted can describe the two peaks and the hollow between them.

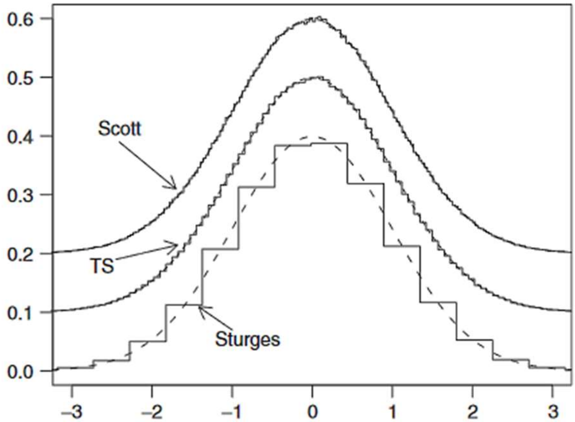


Figure 11 - Example of three rules on a normal sample of size 10^6 [57]

$$h_{scott} = \left(\frac{6}{n\int f'(x)^2 dx}\right)^{1/3} \approx 3.5\sigma n^{-1/3} \tag{15}$$

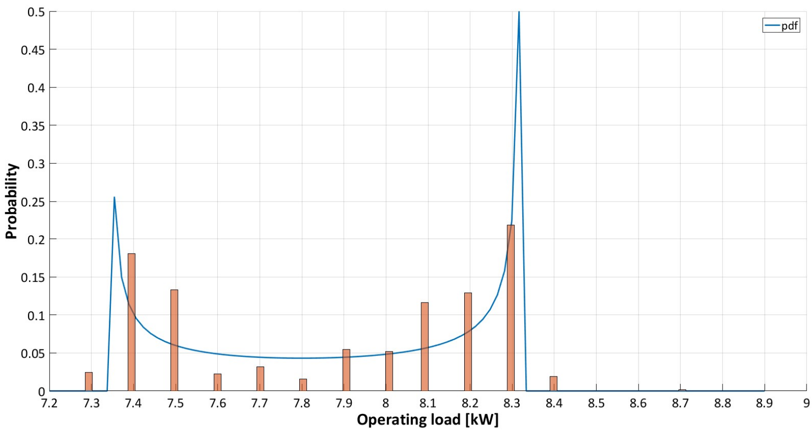


Figure 12 – Continuous distribution for lighting system operating load

However, this distribution does not fit the tails of the sample, as it happens with a discrete distribution, instead. Nevertheless, accepting this approximation, this distribution can be used to describe the sample.

Here definitions for both discrete random variables and continuous ones are reported to allow a better understanding of what above.

- Discrete random variable:

A random variable X is discrete if it takes countably many values $\{x_1, x_2, ...\}$. We define the probability function or probability mass function for X as in equation *(16)*.

$$f_X(x) = \mathbb{P}(X = x) \tag{16}$$

Thus, $f_X(x) \geq 0$ for all $x \in \mathbb{R}$, and $\sum_i f_X(x_i) = 1$. The CDF of X is related to f_X, as proposed in equation *(17)*.

$$F_X(x) = \mathbb{P}(X \leq x) = \sum_{x_i \leq x} f_X(x_i) \tag{17}$$

- Continuous random variable:

A random variable X is defined as continuous if there exists a function f_X such that $f_X(x) \geq 0$ for all x, $\int_{-\infty}^{\infty} f_X(x)dx = 1$ and for every $a \leq b$ is satisfied equation *(18)*.

$$\mathbb{P}(a \leq X \leq b) = \int_a^b f_X(x)dx \tag{18}$$

The function f_X is called the probability density function. Furthermore, we have that:

$$F_X(x) = \int_{-\infty}^{x} f_X(x)dt \tag{19}$$

and $f_X(x) = F'_X(x)$ at all points x at which F_X is differentiable.

In the following paragraphs, several methods are proposed in order to identify the distribution which best fit a certain data sample.

These methods to identify the distributions associated to each random variable are:

- The method *based on designer knowledge* or manufacturer information,
- A method based on *field measurements* and the use of a *Perason's chart*,
- Another method based on *measurements*, which adopts the goodness of fit *maximum likelihood test* to discriminate between distributions,
- And, finally, a method based on *measurements*, which involves the use of *neural networks* to discriminate between distribution.

The performances of these methods have been tested and compared based on experimental readings obtained from a measurement campaign on a naval vessel. In the following figures, these field are reported and described. The first measurement sample is reported in Figure 13, where the operating load of a lighting system is shown. The corresponding is here reported in Figure 14. Moreover, field measurements of a HVAC substation are reported in Figure 15 and the corresponding histogram in Figure 16.

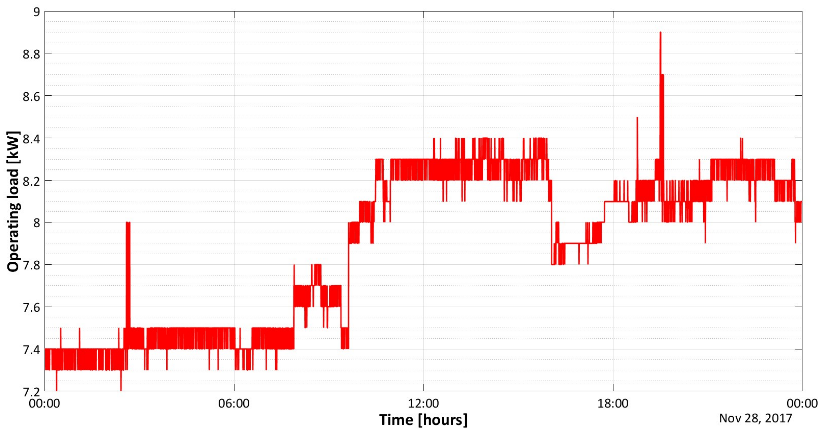


Figure 13 – Experimental measurement for lighting system operating load

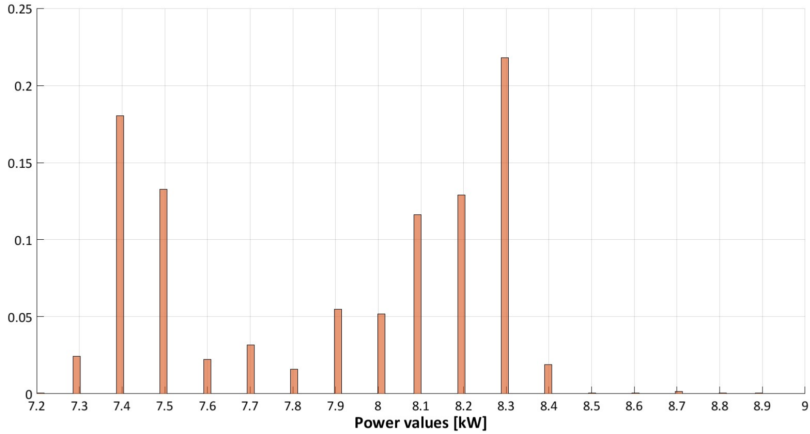


Figure 14 – Histogram for lighting system

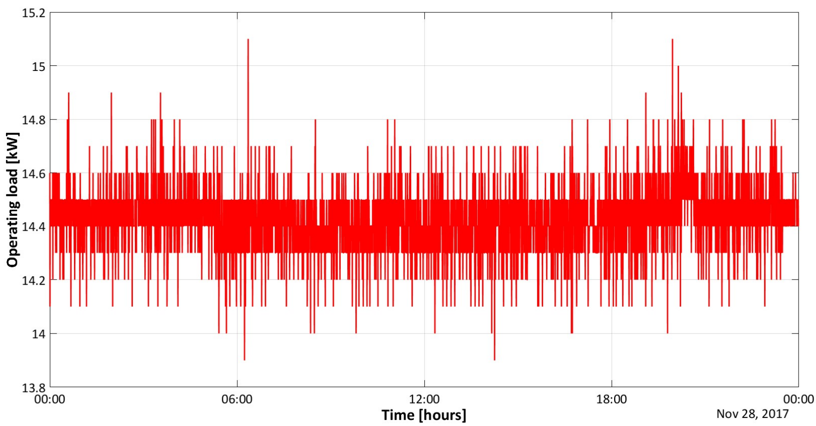


Figure 15 - HVAC system operating load field measurement

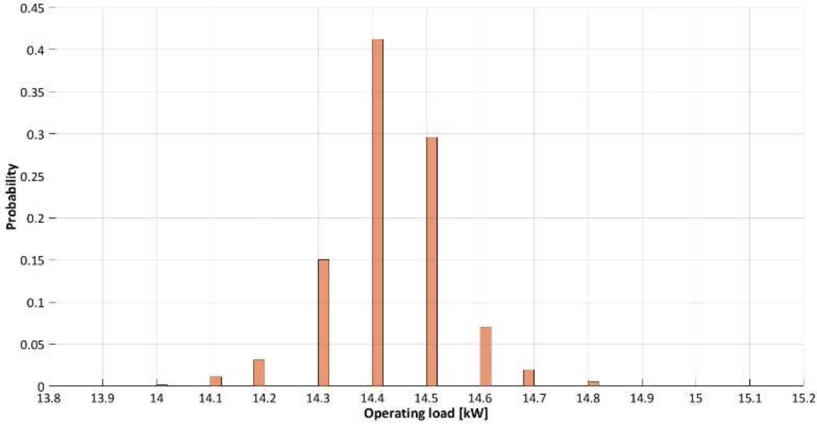


Figure 16 - Histogram for the operating load field measurement of the HVAC system

3.6.1 Characterization based on knowledge

The *"based on knowledge"* method applies the knowledge of the designer or, more in general, of who performs the EPLA. In this perspective, this method adopts information available from personal knowledge, manuals, manufacturer's information and literature in order to select the distribution, and its parameters, which best fit a consumer behaviour.

This method can be easily applied (i.e. usually when no experimental readings are available [34], [58]). In this method, four probability distribution functions can be applied, depending on the random variable that is described.

- <u>Discrete distribution</u>

The discrete distribution is the first function that can be applied to this method. Typical discrete probability density function and its cumulative distribution function are proposed in Figure 17 and in Figure 18.

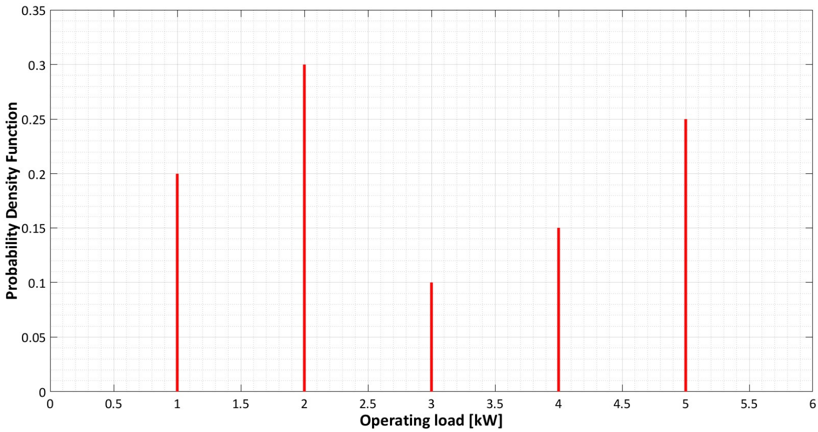


Figure 17 - Discrete probability density function of the operating load

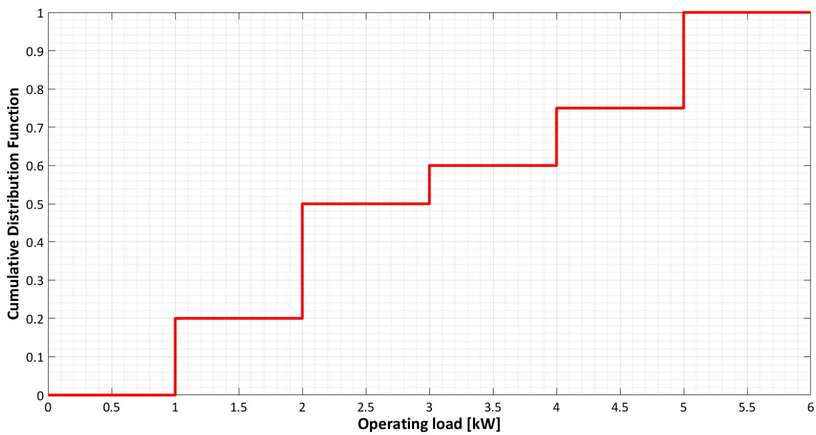


Figure 18 - Discrete cumulative distribution function of the operating load

Similar discrete probability distributions can be applied to describe the behaviour of load characterized by constant values of power absorbed (e.g.

as lighting system), loads with states (e.g. where the probability of occurrence of each state is described by a specific *"spike"* or *"impulsive probability"*).

At design phase, in the case the input information adopted to model these loads are deterministic factors (e.g. load factor or utilization factor), the operating load of a device (or a group of devices) can be modeled with a discrete distribution. In these conditions, the operating load can be identified by a combination of random variables such as state and power absorbed (e.g. as proposed in Figure 17 for the lighting system where state and power absorbed are conditioned random variables).

- Uniform probability distribution

Furthermore, the uniform probability distribution function is the second one that can be adopted in order to model the random variables. The uniform distribution (e.g. also known as rectangular) is continuous and assumes the same value of probability between a minimum and a maximum value of the variable, as proposed in Figure 19 and Figure 20. This distribution is defined by two parameter, *a* and *b*, which are the minimum and maximum value of the random variable (e.g. equal to 4 and 8 kW in Figure 19 and Figure 20).

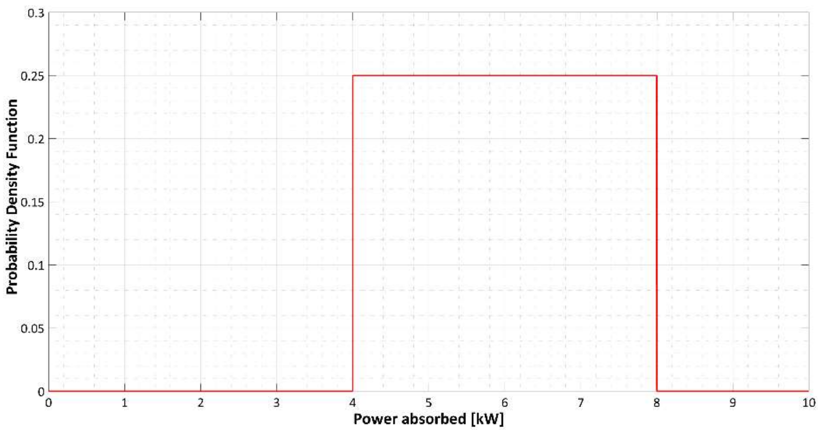


Figure 19 - Uniform probability distribution function of the power absorbed

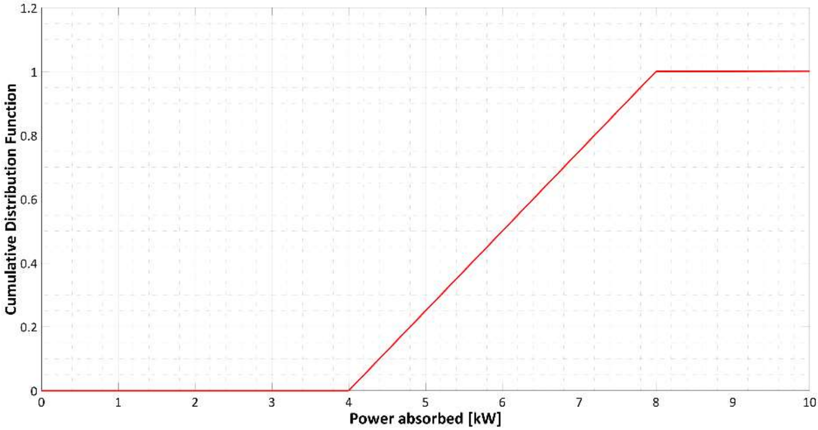


Figure 20 –Cumulative uniform distribution function of the power absorbed

In *(20)*, the equation for the probability density function of a typical uniform distribution is proposed.

$$f(x) = \begin{cases} \dfrac{1}{b\text{-}a} & \text{for } a \leq x \leq b, \\ 0 \text{ for } x < a \text{ and } x > b \end{cases} \tag{20}$$

The uniform distribution can be useful to model those variables that present the same probability of occurrence between a minimum and a maximum value. Furthermore, in early stages of design this is the most appropriate PDF to use, when no detailed information are available about the loads.

- Triangular probability distribution

On the other hand, once more detailed information about the loads are available, a triangular distribution may reflect better these additional information, as proposed in Figure 21 and Figure 22. In fact, in comparison with the uniform one, the triangular distribution can also account for the most probable value (e.g. the modal value identified with the letter "*c*") between the minimum *a* and the maximum *b*. In Figure 21, for example, the modal value is close to 150 kW, which identifies the normal loading condition for this device. Moreover, the minimum and maximum power absorbed are equal to 125 kW and 172 kW, respectively.

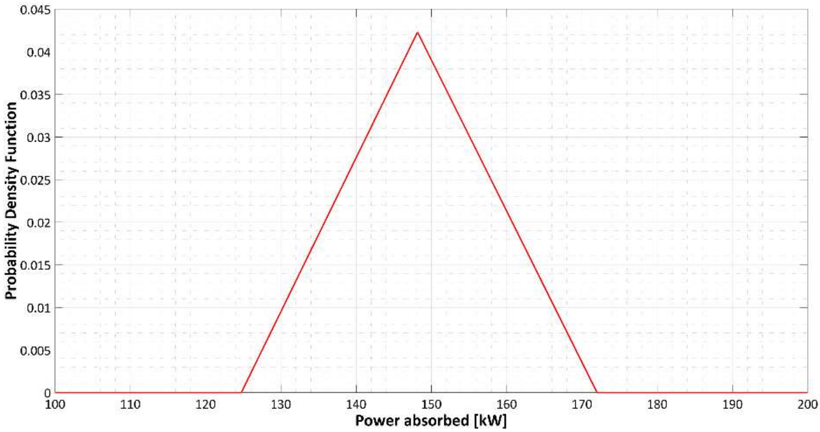


Figure 21 - Triangular probability density function of the power absorbed

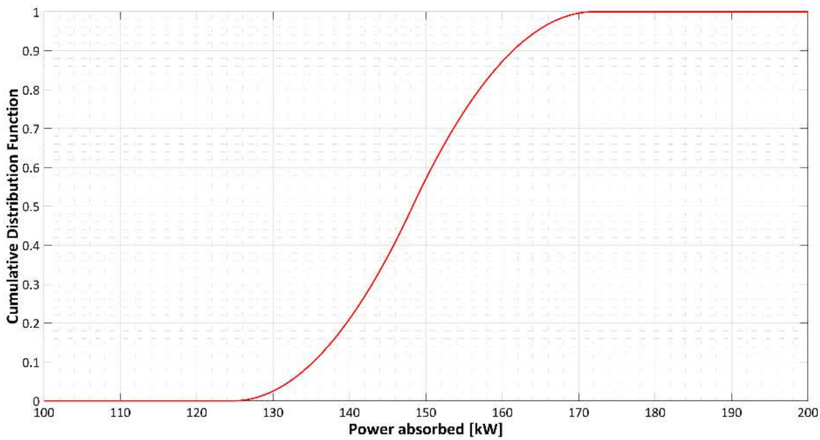


Figure 22 - Cumulative triangular distribution function of the power absorbed

The closer is the power absorbed to the modal value c the greater is its probability of occurrence, as shown in Figure 21 (e.g. this can be a typical distribution for compressors, pumps or motors, when no experimental readings are available).

In *(21)*, the mathematical formulation for this distribution is proposed. Where, a, b and c are the minimum, maximum and modal values of the random variable, respectively.

$$f(x) = \begin{cases} \dfrac{2\cdot(x-a)}{(b-a)(c-a)} & for\ a \leq x \leq c, \\ \dfrac{2\cdot(b-x)}{(b-a)(b-c)} & for\ c \leq x \leq b \\ 0\ for\ x < a\ and\ x > b \end{cases} \tag{21}$$

- <u>Normal probability distribution</u>

Finally, the last distribution that can be applied in this method to characterize the behaviour of the random variables for each electric devices on board a ship is the Normal distribution function. The Normal probability density function and its cumulative distribution function have already been proposed in Figure 5 and Figure 6, respectively. The mathematical formulation for the probability density function is reported in equation *(22)*. Where, the main parameters of this distribution are the mean value μ and the variance σ^2. These values are defined in equations *(23)* and *(24)*, respectively.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{(x-\mu)^2}{2\sigma^2}} \tag{22}$$

$$\mu = \int_{-\infty}^{\infty} x \cdot f(x)\ dx \tag{23}$$

$$\sigma^2 = \int_{-\infty}^{\infty} (x-\mu)^2 \cdot f(x)\ dx \tag{24}$$

Although other distributions can be adopted in this methodology to describe the random variables, in the context of the early stages of design or in case of lack of experimental readings, the proposed distributions can model each random variable when no experimental readings are available.

In Table 3, the possible distributions that can be applied in this approach to describe the main random variables identified in *3.5.4* are summarized. However, further distributions (e.g. Bernoulli and Rayleigh) are also proposed to describe specific random variables, e.g. power absorbed, dependency to the configuration or exogenous variables. As already stated, the proposed methodology combines knowledge from different sources in order to select the probability distribution function that can best fit the behaviour of certain random variables, in the absence of field measurements. Although the models applied to these variables are fairly simple, they still provide enough information to allow the use of the probabilistic method to perform the EPLA.

Differently from what has just been introduced and explained, when field measurements are available, other approaches can be used to select which distribution best fits each random variable. Some of these approaches are proposed and describe in the following paragraphs.

TABLE 3 –PROBABILITY DENSITY FUNCTIONS SELECTED FOR EACH MODEL

Model	**Random variable**	**PDF type**
Constant load	State (on/off)	Discrete
	Power absorbed	Discrete, Bernoulli[3]
Load with states	State (on/off)	Discrete
	Power absorbed	Discrete, Bernoulli, Uniform, Triangular, Normal
	Dependency to the configuration	Discrete, Bernoulli
	Exogenous variables	Discrete, Normal

[3] *Defined in appendix A as Bernoulli distribution*

	State (on/off)	Discrete
Continuous variable load	Power absorbed	Uniform, Triangular, Normal, etc.
	Dependency to the configuration	Discrete, Bernoulli
	Exogenous variables	Discrete, Normal, Rayleigh[4], etc.

3.6.2 Characterization based on measurement, the Pearson's chart

Distributions discrimination problem has been deeply studied in statistics, due to its significant importance for modelling asset prices or macroeconomic variables, such as monetary inflation. Nowadays, there exists a considerable amount of literature on evaluating density forecast models. However, being able to choose a suitable distribution even for a preliminary analysis has remained a considerable problem.

In this paragraph, a method based on the technique developed by Pearson is proposed in order to correctly select the probability distribution functions that best fit the datasets [59]. The reason for considering this particular approach is that the system proposed by Pearson is a parametric family of distributions with easily expressible density functions, which can be used to model a wide scale of distributions with various skewness and kurtosis [60]-[62]. These features make the family amenable to both theoretical and empirical problems where density functions must be expressed explicitly. The selection approach is based on the use of two criteria, which are able to discriminate between the main types of distributions and the interesting subtypes of the system with various restrictions on the support of the variable.

[4] *Defined in appendix A as Rayleigh distribution*

Historically, in the context of financial time series analysis, several distributions have been proposed to model non-normality especially due to asymmetry and leptokurtosis[5] [63]-[67]. The reason why the Pearson's approach is useful, in the perspective of statistical characterization of experimental readings, is that the criteria are quickly computed as functions of the first four central moments. Thus making the technique applicable to both filtering and Bayesian modeling problems, where the ability to quickly choose a convenient distribution is of great importance, as it happens for the probabilistic approach to EPLA.

Karl Pearson was the first to formulate and develop a generalized family of frequency curves, which would satisfactorily fit almost all distributions encountered [68], [69]. This family of curves is hereafter named as Pearson system of curves (or just Pearson system).

In his studies [59] and [70], Pearson noted that the empirical distribution for homogenous populations have a single mode (i.e. hypothesis A) and a high order contact at the extremities (i.e. hypothesis B) of the horizontal axis.

Therefore, if $f(x)$ denotes the probability density function for such a distribution, then equation *(25)* is verified when:

A. $x = M$, where M is the mode,
B. when $f(x) = 0$.

$$\frac{df}{dx}=0 \tag{25}$$

A differential equation satisfying the above conditions is proposed in *(26)*. In this context, there is no need to consider terms beyond c_2x^2 in the denominator of the right hand side, as the differential equation *(26)* is found in generating curves varying shapes and forms.

---

[5] *Leptokurtic is a statistical distribution where the points along the X-axis are clustered, resulting in a higher peak, or higher kurtosis, than the curvature found in a normal distribution.*

$$\frac{1}{f(x)}\frac{df(x)}{dx} = \frac{x - \alpha}{c_0 + c_1 x + c_2 x^2} \tag{26}$$

A general solution of the above equation *(26)* is given in *(27),* where k is a constant.

$$f(x) = k \cdot e^{\int \frac{(x - \alpha)\, dx}{c_0 + c_1 x + c_2 x^2}} \tag{27}$$

In accordance with the values of particular parameters, twelve types of curves are obtained as the solution of equation *(27)*. These curves are often used to approximate experimental distributions [71]-[73]. Several well-known distributions belong to the Pearson family, for example: Normal, Gamma, Beta and Student's *t*-distribution. As already told, the system was introduced by Karl Pearson [59], in 1895 and comes from a set of four-parameter probability density functions, which are solutions to the differential equation *(26)*.

A reason why the Pearson system is particularly appealing is the direct correspondence between the parameters and the central moments ($\mu_1, \ldots, \mu_4$) of the distribution [74], as proposed in equations *(28)-(30)*. Where the two moment relations proposed in equation *(31)-(32)* denote the square of the skewness[6] and the kurtosis, respectively.

$$c_0 = - \frac{\mu_2 \left(4\mu_2\mu_4 - 3\mu_3^2\right)}{A} = - \frac{\mu_2 \,(4\beta_2 - 3\beta_1^2)}{A'} \tag{28}$$

$$c_1 = - \frac{\mu_3 \left(\mu_4 + 3\mu_2^2\right)}{A} = - \frac{\mu_2^{\frac{1}{2}} \beta_1 (\beta_2 + 3)}{A'} \tag{29}$$

$$c_2 = - \frac{\left(2\mu_2\mu_4 - 3\mu_3^2 - 6\mu_2^{23}\right)}{A} = - \frac{(2\beta_2 - 3\beta_1^2 - 6)}{A'} \tag{30}$$

---

[6] *Skewness and kurtosis are defined in appendix A in this thesis.*

$$\beta_1^{\,2} = \frac{\mu_3^{\,2}}{\mu_2^{\,23}} \tag{31}$$

$$\beta_2 = \frac{\mu_4}{\mu_2^{\,2}} \tag{32}$$

The scaling parameters A and A' proposed in *(28)-(30)* are obtained as reported in equations *(33)* and *(34)*.

$$A = 10\mu_4\mu_2 - 18\mu_2^{\,3} - 12\mu_3^{\,2} \tag{33}$$

$$A' = 10\beta_2 - 18 - 12\beta_1 \tag{34}$$

When those estimated from the experimental readings replace the theoretical central moments, the above equations define the moment estimators for the Pearson parameters α, c_0, c_1 and c_2.

As proposed in Figure 23, there exists a limit for all frequency distributions under the line $\beta_2 - \beta_1^{\,2} - 1 = 0$. This is the impossible region for all distribution (e.g. no distribution can assume those values of skewness and kurtosis).

In Figure 23, distributions Type I and II are Beta distributions of first kind. Notation I(J;U) is referred to J-shaped and U-shaped distributions and I(M) to unimodal ones. The boundary of distributions I(J;U) is proposed in equation *(35)*. Type III distributions identify the Gamma distributions with a line limit reported in equation *(36)*. Type VI, on the other hand, denotes the Beta distributions of the second kind. Type V can be defined by equation *(37)* and Type IV is obtained when $c_0 + c_1x + c_2x^2 = 0$ has a complex roots and Type VII includes Student's *t*-distribution.

Despite the mathematical formulation, this is a quickly and simple method to discriminate the distribution for specific random variables. In fact, as widely explained, it requires only the evaluation of skewness and kurtosis of the sample to select which distribution is the fittest one.

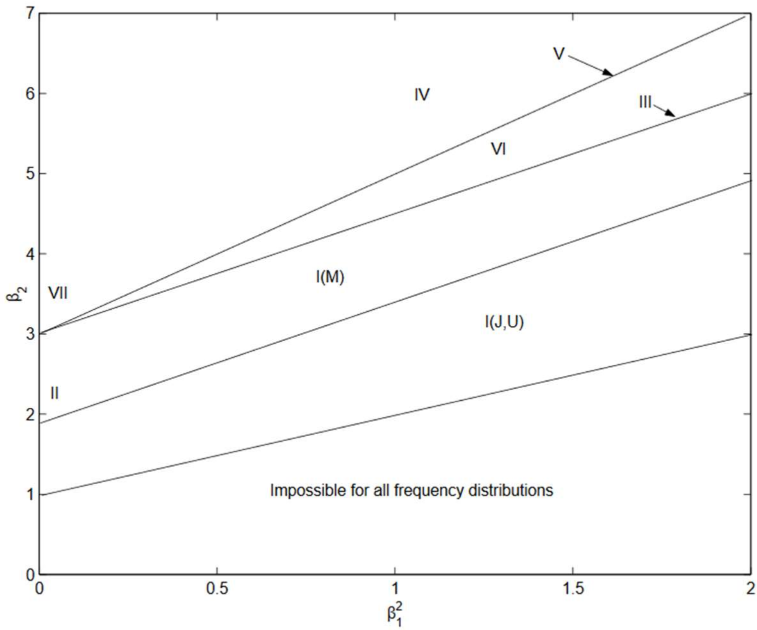


Figure 23 - Pearson's chart [60]

$$4(4\beta_2-3\beta_1^2)(5\beta_2-6\beta_1^2-9)^2=\beta_1^2(\beta_2+3)^2(8\beta_2-9\beta_1^2-12) \tag{35}$$

$$\beta_2-\frac{3}{2}\beta_1^2-3=0 \tag{36}$$

$$\beta_1^2(\beta_2+3)^2=4(4\beta_2-3\beta_1^2)(2\beta_2-3\beta_1^2-6) \tag{37}$$

Theoretically, other types of distributions can be applied to this method by considering all the possible values assumed by their skewness and kurtosis. In this perspective, useful distributions such as the Normal, Poisson, Rayleigh, Weibull and Gumbel can be implemented to the Pareto system and adopted to model the random variables identified in paragraph *3.5.4*.

Typical skewness and kurtosis indexes are summarized in Table 4 for several distributions that can be adopted to correctly translate into statistical law the behaviour of the random variables identified.

TABLE 4 - SKEWNESS AND KURTOSIS INDEXES SUMMARY

Distribution	Skewness	Kurtosis
Normal Gaussian	0	3
Normal-inverse Gaussian	$3\sqrt{\frac{\mu}{\lambda}}$	$3+\frac{15\mu}{\lambda}$
Log-Normal	$(\omega-1)^{1/2}(\omega+2)$	$\omega^4+2\omega^3+3\omega^2-3$
Student-*t*	0	$3+\frac{6}{\nu-4}$
Gamma	$\frac{2}{\sqrt{\alpha}}$	$3+\frac{6}{\alpha}$
Exponential	2	6
Generalized Pareto	$\frac{2(1-c)\sqrt{1+c}}{1+3c}$	$\frac{3(1+2c)(3-c+2c^2)}{(1+3c)(1+4c)}$
Beta	$2(p-q)\cdot$ $\cdot\sqrt{p^{-1}+q^{-1}+(pq)^{-1}}\cdot$ $\cdot(p+q+2)$	$3(p+q+1)\cdot$ $\cdot\{2(p+q)^2+pq(p+q-6)\}\cdot$ $\cdot[pq(p+q+2)(p+q+3)]^{-1}$
Rayleigh	$\frac{2\sqrt{\pi}(\pi-3)}{(4-\pi)^{3/2}}\approx 0.631$	$-2\frac{3\pi^2-12\pi+8}{(4-\pi)^2}\approx -0.245$
Weibull	$\frac{\lambda^3\Gamma\left(1+\frac{3}{k}\right)-3\mu\sigma^2-3\mu^3}{\sigma^3}$	$\frac{\lambda^4\Gamma\left(1+\frac{4}{k}\right)}{\left[\lambda^2\Gamma\left(1+\frac{2}{k}\right)\right]^{3/2}}$
Gumbel	$\frac{12\sqrt{6}\xi(3)}{\pi^3}\approx 1.14$	$\frac{12}{5}$

In order to allow a full understanding of what presented above, the probability density functions of these distributions are here proposed from equation *(38)* to equation *(47)*, respectively.

$$f_x(x)= \frac{x}{\sigma^2} e^{-\frac{x^2}{2\sigma^2}} \tag{38}$$

$$f_x(x|\mu,\lambda)= \left[\frac{\lambda}{2\pi x^3}\right]^{1/2} e^{-\frac{\lambda}{2\mu^2 x}(x-\mu)^2}, x > 0 \tag{39}$$

$$f_x(x)=\left[(x-\vartheta)\sqrt{2\pi}\sigma\right]^{-1} e^{-\frac{1}{2}\frac{\{log(x-\theta)-\zeta\}^2}{\sigma^2}}, x > \theta \tag{40}$$

$$f_x(x)=\frac{(x-\gamma)^{\alpha-1} e^{-(x-\gamma)/\beta}}{\beta^\alpha \Gamma(\alpha)}, \alpha >0, \beta >0;x > \gamma \tag{41}$$

$$f_x(x)=\sigma^{-1} e^{-\frac{(x-\theta)}{\sigma}}, x>\theta; \sigma >0 \tag{42}$$

$$f_X(x)=\begin{cases} k^{-1}(1-cx/k)^{c^{-1}-1}, c \neq 0 \\ k^{-1}e^{-x/k}, c = 0 \end{cases} \tag{43}$$

$$f_y(y)=\frac{1}{B(p,q)}\frac{(y-a)^{p-1}(b-y)^{q-1}}{(b-a)^{p+q-1}}, a \leq y \leq b \tag{44}$$

$$f_z(z)= \frac{z}{\sigma^2} e^{-\frac{z^2}{2\sigma^2}}, Z = \sqrt{X^2+Y^2} \tag{45}$$

$$f_x(x)= \frac{k}{\lambda^k} x^{k-1} e^{-\left(\frac{x}{\lambda}\right)^k} \tag{46}$$

$$f_x(x)= e^{-(x+e^{-x})} \tag{47}$$

This method has been tested based on the field measurements reported in Figure 13 and Figure 15. Considering for example the lighting system, a continuous four-parameter Beta distribution has been selected as the fittest to the sample data, as it is shown in Figure 12.

Moreover, considering the field measurement in Figure 15, the behaviour of the HVAC system has been associated to a Normal distribution, as reported in Figure 24.

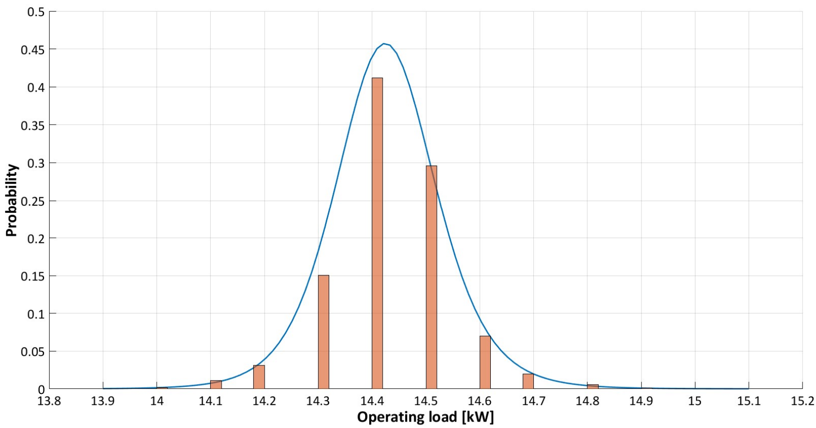


Figure 24 - Normal distribution associated to the HVAC system behaviour

3.6.3 Characterization based on measurement, the goodness of fit tests

The problem of discriminating from which distribution is generated a certain data sample has been deeply studied in financial statistics. Usually, this is faced by adopting the *"Goodness of fit tests"*, starting from the hypothesis of normality of the sample.

However, there are several problems in adopting this hypothesis of normality. Therefore, it is important to be able to discriminate between the hypothesis of normality and the hypothesis of other distributions, in order to select the *"fittest"* model. The goodness of fit test requires the comparison between two or more statistical hypothesis, and the selection of the distribution is performed based on the data sample considered.

Generally, a statistical hypothesis is a statement based on the value of the statistical parameter considered on a single or multiple population. The problem formulation always involves two mutually exclusive statements:
- the Null hypothesis H_0, which is the hypothesis assumed true at the beginning and subjected to test,
- the Alternative hypothesis H_1, which is the contrary assumption compared to the previous one.

In the perspective of discriminating if a data sample belongs to a specific distribution, this should be specified in the Null hypothesis. To proceed with the test it is required to define the region of acceptance of the hypothesis, which corresponds to the set of statistical values that would lead to accept H_0 if true, with an error probability equal to α. Therefore, the probability of the confidence interval would be equal to $1-\alpha$.

Confidence interval and acceptance region are strictly related. In fact, the confidence interval is composed of all those values that would lead to accept the Null hypothesis once α and the sample size n have been fixed. Accordingly, once the Null and the alternative hypothesis have been defined, a set of values compatible with the first one is defined and then it is possible to proceed by verifying whether the empirical value is compatible with the set of values that are consistent with this hypothesis.

Two errors are possible in the test of hypothesis:
- first type error, probability to reject the Null hypothesis when this is true $\alpha = P(Acceptance\ of\ H_1/H_0\ true)$,
- second type error, probability to accept the Null hypothesis when the alternative one is true, $\beta = P(Acceptance\ of\ H_0/H_1\ true)$.

Assuming a random sample $X_1, X_2, \ldots, X_n$ of random independent variables identically distributed from a continuous univariate distribution with unknown probability density function $f(x,\theta)$; where $\theta = (\theta_1, \theta_2, \ldots, \theta_p)$ is a vector of real parameters. The formal test to verify whether the observed sample belongs to a population with Normal distribution, can be formulated with a test of composed hypothesis, as proposed in *(48)* and (49) for the Null hypothesis and the Alternative one, respectively.

$$H_0 : f(x,\Theta) \in N(\mu,\sigma) \tag{48}$$

$$H_1 : f(x,\Theta) \notin N(\mu,\sigma) \tag{49}$$

Performing the first test between the two hypothesis, every test should consider the same probability of rejection of the Null hypothesis whether this is true. Namely, they should have the same error of the first type α. By changing the level of significance, there is the possibility that the test leads to different results. Due to this reason the *p*-value is calculated, which measures the probability to observe values of the test greater than the sample value, whether the Null hypothesis is true.
The *p*-value may change between 0 and 1. When it is equal to 1 means that the Null hypothesis is maximally to be supported, vice versa whether it assumes value 0. However, the following conditions may occur:
- *p*-value $< \alpha$, rejection of the Null hypothesis,
- *p*-value $> \alpha$, acceptance of the Null hypothesis,
- *p*-value $= \alpha$, indecision situation.

To verify the validity of a statistical test, or in other words its reliability, it is possible to calculate the *"power of the test"* that is the probability of the test to fall into the region of rejection of the Null hypothesis when the alternative one is true. Thus, the power of the test is the probability proposed in *(50)*.

$$\mathrm{P}(reject\ H_0|H_1 true) = 1 - \beta \tag{50}$$

The evaluation of the power of the test requires the knowledge of the sample distribution under the Alternative hypothesis and, more the value is close to 1, more reliable is considered the test.

The power of a test depends on several aspects, the most significant are:
- the data sample dimension *n*. In fact, the greater is the dimension the greater is the power,

- the level of significance α. The greater is this level, the greater is the power of the test, again. It is to be noted that, the greater is α smaller is the region of acceptance,
- the real value of the tested parameter. The power of a statistical test is a growing function of the difference between the real value and the estimated one, considered in absolute value.

Through the calculation of the power, it would be possible to compare different statistical tests in order to research the one with "more power" and, therefore, the most reliable in the perspective to choice a specific distribution for a given set of data. Over the years, there have been many studies focused on the selection of the best method to discriminate from which distribution comes a data sample. However, it is not possible to define which one is the best. Considering the distributive characteristics of the variables identified in 3.5.4, in particular of the Skewness and Kurtosis, as well as the importance to correctly model the tails of the distribution (e.g. which identify the extreme value probability), it is needed to select the test which better describe the extreme value probability.

In this context, the well-known *"maximum likelihood estimation"* method is here introduced.

- <u>Maximum likelihood method</u>

The selection of a certain distribution adopting the maximum likelihood estimation (MLE) method was firstly proposed by Cox in 1961, in the perspective to discriminate between two separated models [75]. Moreover, Bain and Egenhardt, in 1980, adopted the MLE method to discriminate between the Weibull and Gamma distributions [76]. In order to describe the testing hypothesis method through the ratio of maximized likelihoods, the likelihood function is first introduced. Considering a sample $x_1, x_2, \ldots, x_n$ extracted from a population X, which distribution depends on the parameter θ. The likelihood function is indicated with $L(\theta)$, and represents the probability to observe the sample varying the parameter θ. Under the hypothesis that the observations are independent and identically distributed, it is possible to define the likelihood function as proposed in equation *(51)*.

$$L(\theta) = P(X_1=x_1,\ldots,X_n=x_n|\theta) = \prod_{i=1}^{n} f(x_i|\theta)\,, \qquad (51)$$

Where, $f(x_i|\theta)$ is the probability density function. The likelihood function is adopted to build different statistical tests, among which there is the one based on the ratio of the *"maximized probabilities"* that measures the difference between the maximum values of the non-constrained and the constrained log-likelihood.

- Validation of the Maximum likelihood method

A specific distribution has been selected to generate the reference data sample, which is applied to the Maximum Likelihood Estimation (MLE) method. The percentages of probability of the method to select the right distribution for the data sample under exam are reported in the following tables. To test this method, the Log-Normal, Inverse-Normal, Generalized Pareto, Exponential, Gamma and Gumbel distributions have been considered.

- Comparison between Log-Normal, Gamma and Generalized Pareto distributions

The first test to validate this approach considers three distributions. The data samples are generated from all the three distributions and tested for all the possible combinations, as proposed in Table 5. The percentage of selection of a distribution rather than the others are proposed in Table 5. The total probability to select the right distribution, in this case, is equal to 0.7674 (e.g. obtained by summing the values reported in the diagonal of Table 5).

TABLE 5 - DISTRIBUTION'S DISCRIMINATION WITH MLE, FIRST CASE

Distributions	Log-Normal	Gamma	Generalized Pareto
Log-Normal	0.2362	0.0938	0.0033
Gamma	0.1059	0.2168	0.0107
Generalized Pareto	0.0046	0.0144	0.3144

- <u>Comparison between Log-Normal, Gamma and Inverse-Normal distributions</u>

The same condition proposed in the first test are here considered. However, the Inverse-Normal distribution has been considered for the test, instead of the Generalized Pareto considered in the first. The total probability to select the right distribution, in this second case, is equal to 0.4947. All the resulting probabilities are summarized in Table 6.

TABLE 6 - DISTRIBUTION'S DISCRIMINATION WITH MLE, SECOND CASE

Distributions	Log-Normal	Gamma	Inverse-Normal
Log-Normal	0.0935	0.0918	0.1481
Gamma	0.0479	0.2172	0.0682
Inverse-Normal	0.0793	0.0700	0.1840

- <u>Comparison between Log-Normal, Inverse-Normal and Exponential distributions</u>

Regarding the third test, it is possible to note that the probability of this method to select the right distribution is equal to 0.6858. All the probabilities associated to the selection of each distribution and obtained in the test are here proposed in Table 7.

TABLE 7 - DISTRIBUTION'S DISCRIMINATION WITH MLE, THIRD CASE

Distributions	Log-Normal	Inverse-Normal	Exponential
Log-Normal	0.1653	0.1646	0.0034
Inverse-Normal	0.1322	0.1984	0.0027
Inverse-Normal	0.0059	0.0054	0.3220

- <u>Comparison between Log-Normal, Inverse-Normal and Gumbel distributions</u>

Finally, this last test, considers all the other distribution not already tested. The probability to select the right distribution is equal to 0.6990. The probabilities of selection of each distributions in relation to the reference samples are summarized in Table 8.

TABLE 8 - DISTRIBUTION'S DISCRIMINATION WITH ANN, FOURTH CASE

Distributions	Log-Normal	Inverse-Normal	Gumbel
Log-Normal	0.1878	0.1456	0
Inverse-Normal	0.1528	0.1805	0
Gumbel	0.0000	0.0001	0.3331

These tests can also be performed for more than three distributions. However, a further validation of this methodology is not in the interest of this chapter.

This method has been applied to the field measurements in Figure 13 and Figure 15, in order to verify its performances. Results of this test are proposed in Figure 25 and Figure 24 for the lighting and HAVC system, respectively.

Considering the lighting system, a non-parametric Kernel distribution has been selected applying the maximum likelihood method. It should be noted that, the distribution selected with this method is different from the one selected adopting the Pearson' chart (i.e. the maximum likelihood selects a non-parametric Kernel and the Pearson's chart a four parameters Beta distribution).

On the other hand, the HVAC system presents a behaviour that is associated to the same Normal distribution selected adopting the Pearson's chart method.

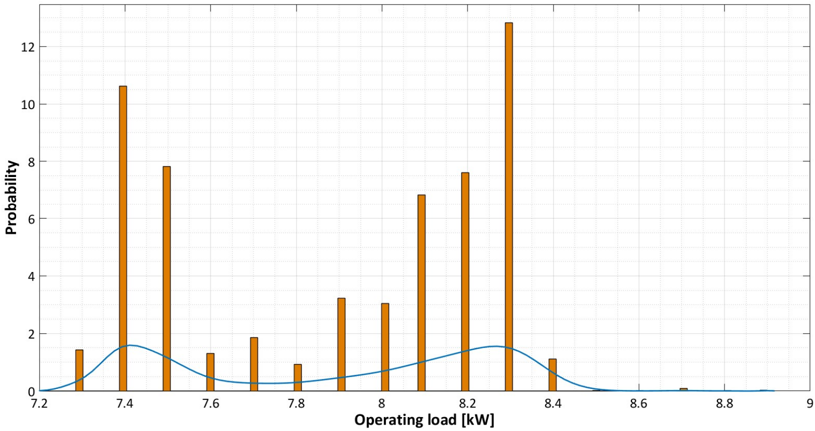


Figure 25 – Non-parametric Kernel distribution for the lighting system operating load adopting maximum likelihood method

3.6.4 Characterization based on measurement, use of artificial neural networks to discriminate distributions

Recently, in [77] and [78] the use of artificial neural networks (ANN) has been suggested. This approach is proposed as an instrument to discriminate between two or more distributions. The performances of ANN as a goodness of fit tests have been compared in [79] to the results obtained in [80] for eight normality tests for different sample sizes (e.g. n = 20, n = 50 and n = 100).

Neural networks are computational systems inspired by biological processes. These are born with the purpose of imitating the behaviour of the human brain that is characterized by the interconnection of cells, called neurons. A biological neuron consists of a cell body and branched extensions that are referred to as dendrites, and it is through these that the neuron receives electrical signals from other neurons.

Each neuron also possesses a stringy extension called axon, at whose extremity it branches, forming terminals through which electrical signals are transmitted to other cells. Between the terminal of an axon and the receiving cell there is a space that is overcome by the signals through chemical substances, called neurotransmitters [81]-[87]. The point that connects the terminal with the dendrite is called the synapse. A neuron "activates" transmits an electrical impulse along its axon when a difference in electrical potential occurs between the inside and the outside of the cell, the electric impulse causes the release of a neurotransmitter by the terminals of the axon, which in turn can influence other neurons. The comparison between the biological neuron and the artificial one is proposed in Figure 26.

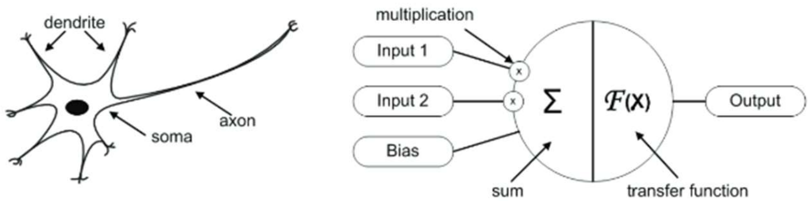


Figure 26 - Graphic representation of biological and artificial neurons

The neuron is the basic element for calculating the network and, as proposed in Figure 26, it consists of:

- a set of synapses or connections each of which is characterized by a weight (e.g. synaptic efficacy), and unlike the human model, the artificial model can have both negative and positive weights,
- an adder adding up the input signals weighed by the respective synapses, producing a linear combination of said inputs,
- an activation function to limit the amplitude of a neuron's output. Typically, for convenience, the width of the outputs belongs to the interval [0, 1] or [-1, 1].

It is also necessary to consider a threshold value, which, according to its positive or negative nature, increases or decreases the net input of the activation function. Regarding the design of a neural network, the steps are:

- the choice of the number and type of unit,
- the determination of the morphological structure,

- the coding of training examples, in terms of inputs (inputs) and outputs (outputs) from the network,
- the initialization and training of weights on interconnections, through the training set.

To explain the operation of the network, we must first consider that this performs different activities. In fact, it evaluates the intensity of each input, adds the various inputs and compares the result with an appropriate threshold, and finally determines the value of the 'output.

Just as a biological neuron receives different inputs through dendrites, the artificial neuron also receives different input values, $i_1, i_2, \ldots, i_n$. All inputs are then added together and the result is the value computed by the artificial neuron, which, if it exceeds a given threshold, produces an output signal U, as proposed in equation *(52)*.

$$U = i_1 + i_n + \ldots + i_n \tag{52}$$

By comparing the output U with a suitable threshold value q, the potential P will be equal to what reported in *(53)*.

$$P = q - U \tag{53}$$

- <u>Feed-forward neural networks</u>

In this network, it is possible to distinguish the input nodes (e.g. input layer) and a layer of output neurons (e.g. output layer). The signal in the network propagates in an acyclic way, starting from the input layer and arriving in the output one.

In the case of one layer forward networks, each neuron is connected only with neurons of the previous layer and, in output, only with the next layer, so there are neither backward connections nor transversal connections, as proposed in Figure 27. On the other hand, in the case of multi-layer forward networks, between the input and output layers there are one or more layers of hidden neurons (e.g. hidden layers). Each layer has connections that come out of the previous layer and enter the next one, so even in this case there are neither cycles nor transversal connections, as shown in Figure 28.

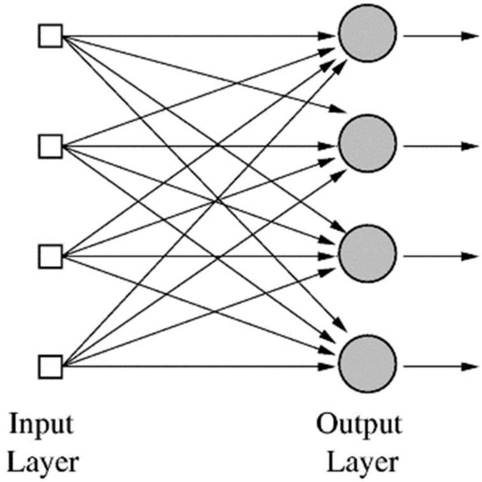


Figure 27 – One layer feed-forward neural network

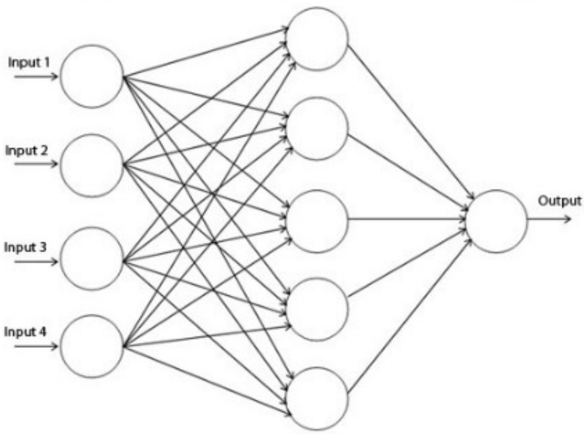


Figure 28 - Multi-layer feed-forward neural network

- <u>Goodness of fit test with feed-forward neural networks</u>

To verify the hypothesis of normality (or other kind of distribution) of a data sample obtained by field measurement, in this thesis the building of a feed-forward neural network is proposed. It consists of n input neurons, a layer of hidden neurons and a single output neuron.

Hereafter, it will be indicated with y_i the generic i^{th} input neuron of the network (e.g. $i = 1,2, ..., n$), with w_{ij}^1 the weights of the connections between the i^{th} neuron of entry and the j^{th} hidden neuron ($j = 1,2, ..., h$), with w_j^2 the weight of the connections between the j^{th} hidden neuron and with S_n the single output neuron. Finally, it is indicated with a_1 and a_2 two activation functions for the neurons. The expression of the exit neuron can then be written as proposed in equation *(54)*.

$$S_n = a_1\left(\sum_{i,j=1}^{h,k} a_2\, y_{(i)} w_{ij}^{(1)}\, w_j^{(2)}\right) \tag{54}$$

For example, in this paragraph, this method it is tested in order to verify the typical normality assumption of a data sample, compared to alternative distributions with the same mean μ and variance σ^2. In this perspective, firstly, it is required to verify the null hypothesis H_0 of normal distribution against the alternative hypothesis H_1 of another distribution. Therefore, the testing procedure is composed of nine main steps:

1) The generation (or just taking the samples in the case measurement are available) of k samples of dimensions n.
2) The generation of k normal (or other test distribution of interest such as those reported in Table 4) samples with dimension n.
3) The ordered samples y_i ($i = 1,2, ..., n$) are considered as input vectors. Moreover, the threshold values are set equal to *0* if the sample comes from a normal distribution. Otherwise, threshold values are set equal to *1,* when generated from alternative distributions.
4) Input vectors are divided for both the hypothesis in three datasets. The first dataset is for the training of the network, the second one, on the other hand, is for validation and, finally, the last one is for the test. These samples have dimensions t, v and ts, respectively (i.e. being $t+v+ts = k$).

5) It is possible to proceed with the training of the network applying the Levenberg-Marquardt algorithm with sigmoid activation functions and minimizing the mean square error.
6) The network is tried on the test set and store the $2 \times ts$ outputs of the network generating the empirical distributions of $S_n|H_0$ and $S_n|H_1$.
7) It is defined a level of significance a and find the threshold T which represents the centile level ($1\text{-}a$) of the null distribution, as proposed in equation *(55)*.
8) The network is tested on the real sample x and, if the output results under the threshold T, the null hypothesis is accepted. Otherwise, the alternative one will be accepted.
9) The sample ratio is calculated in the null hypothesis, which has a larger network output than the true sample, and this represents the value of the p-value of H_0 against H_1.

$$1 - f\,(S_n|H_1 \geq T) = 1 - b \tag{55}$$

The performed simulations have revealed that the distinction between the distributions of the neural test statistic, under the null hypothesis and the alternative one, increases with the sample size and the power is often greater than the level of significance.

The results achieved have underlined that the test of goodness of fit based on the neural network is the most powerful compared to the other tests considered. In fact, the other tests usually present an excellent power just on a specific class of alternatives, despite all the others. The proposed technique can be extended to the choice between more than two alternative distributions. Actually, using for example a network output composed of two neurons, it is possible to formulate a null hypothesis and three alternatives.

- Method validation

To test this method, the same distributions considered in *3.6.3* have been selected. The tests (e.g. consisting of 7000 simulations) have been developed selecting a specific distribution for the reference data sample, which is applied to the method. Results show the percentage of probability of the method to select the right distribution for the data sample under exam. In this perspective, from the examples proposed in the following, it is possible to state that, in this case, the method based on the use of ANN works as good as the one based on the traditional goodness of fit tests proposed in *3.6.3*.

- Comparison between Log-Normal, Gamma and Generalized Pareto distributions

This first test considers three different distribution that can be selected for the reference data sample. By summing the percentage values reported in the diagonal of Table 9 it is possible to highlight that the probability of this method to select the right distribution is equal to 0.7622, compared to the 0.7674 of the method proposed in *3.6.3*.

TABLE 9 - DISTRIBUTION'S DISCRIMINATION WITH ANN, FIRST CASE

Distributions	Log-Normal	Gamma	Generalized Pareto
Log-Normal	0.2329	0.0976	0.0029
Gamma	0.1058	0.2155	0.0120
Generalized Pareto	0.0043	0.0152	0.3138

- Comparison between Log-Normal, Gamma and Inverse-Normal distributions

The second test here proposed considers again three different distribution that can be selected for the reference data sample. Here, it is possible to highlight that the probability of this method to select the right distribution is equal to 0.4947, according with the results proposed in Table 10. This can be compared to the 0.4913 obtained by the method proposed in *3.6.3*.

TABLE 10 - DISTRIBUTION'S DISCRIMINATION WITH ANN, SECOND CASE

Distributions	Log-Normal	Gamma	Inverse-Normal
Log-Normal	0.0903	0.0940	0.1490

Gamma	0.0441	0.2204	0.0688
Inverse-Normal	0.0790	0.0738	0.1806

- Comparison between Log-Normal, Inverse-Normal and Exponential distributions

Concerning the third test, it is possible to highlight that the probability of this method to select the right distribution is equal to 0.6889, according with the results proposed in Table 11.

This, compared to the 0.6858 obtained by the other method, is for the first time higher than the latter.

TABLE 11 - DISTRIBUTION'S DISCRIMINATION WITH ANN, THIRD CASE

Distributions	Log-Normal	Inverse-Normal	Exponential
Log-Normal	0.1516	0.1769	0.0048
Inverse-Normal	0.1158	0.2150	0.0025
Inverse-Normal	0.0056	0.0055	0.3222

- Comparison between Log-Normal, Inverse-Normal and Gumbel distributions

In this last test (e.g. which result are proposed in Table 12), the probability of this method to select the right distribution is again higher than in the other method. The correct selection resulting from the methods are equal to 0.7014 and 0.6990, respectively.

The tests can also be performed for more than three distributions. However, the validations in such conditions is out of the aim of this thesis.

TABLE 12 - DISTRIBUTION'S DISCRIMINATION WITH ANN, FOURTH CASE

Distributions	Log-Normal	Inverse-Normal	Gumbel
Log-Normal	0.1878	0.1456	0
Inverse-Normal	0.1528	0.1805	0
Gumbel	0	0.0001	0.3331

Two tests have been performed to verify the effectiveness of this method and compare its results to those obtained applying the other methods. ANN have been trained adopting six months of measurements for both the systems under exam, with a time steps of 15 seconds. Then, they have been tested for the samples proposed in Figure 13 and Figure 15. The results yielded are the same proposed for the MLE method. In fact, a non-parametric Kernel distribution has been selected for the lighting system and a Normal distribution for the HVAC, as reported in Figure 25 and Figure 24, respectively.

As a conclusion to the statistical characterization of the random variables identified in paragraph *3.5* it is possible to state that all the methods proposed in *3.6* are reliable and effective. Therefore, their application depend on the information available and on the computational time constraints, rather than on their effectiveness.

3.7 Joint and conditional probabilities

The load characterization has been proposed in paragraph *3.5*, where the main random variables that describe the values assumed by the operating load of a device have been described and listed in Table 3. It is possible to highlight that some of the models proposed present joined or conditional probabilities.

In this context, let A, B be events in a probability space. The *conditional probability* of A given B is defined in *(56)*, when $P(B)>0$.

$$\mathrm{P}(A|B)=\frac{\mathrm{P}(A\cap B)}{\mathrm{P}(B)} \tag{56}$$

In other words, the conditional probability $\mathrm{P}(A|B)$ is the fraction of B probability occupied by the $\mathrm{P}(A\cap B)$ probability [88]. Therefore, in the case of measurement of the operating load for a device (e.g. such as the lighting system proposed in Figure 13), this operating load identifies the power absorbed by the load conditioned to its status (i.e. on or off state).

In the case of two *independent events*, A and B, the $\mathrm{P}(A\cap B)$ joint probability is equal to the probability of A multiplied by the probability of B, as proposed in *(57)*.

$$\mathrm{P}(A\cap B) = \mathrm{P}(A) \cdot \mathrm{P}(B) \tag{57}$$

In fact, it is to be noted that, two events are independent if equation *(57)* is valid. In this case, the *joint probability* for two independent event is proposed in *(58)*.

$$\mathrm{P}(A\cap B) = \mathrm{P}(A|B) \cdot \mathrm{P}(B) \tag{58}$$

Compound process are often decomposed into two or more sub-processes, which can operate without influence on one another.

Therefore, it is possible to define the probabilities of the compound events as the product of the corresponding probabilities from the sub-processes. Suppose now that $A_0, A_1, \ldots, A_n$ is a partition of the probability space Ω into disjoint subset, each of nonzero probability. For any event F, it follows what proposed in equation *(59)*.

$$\mathrm{P}(F) = \sum_{i=0}^{n} \mathrm{P}(F|A_i) \cdot \mathrm{P}(A_i) \tag{59}$$

This is the *law of the total probability*, and it is just a reformulation of the counting principle that justifies breaking an ensemble into convenient pieces.

This, is very useful in the case of loads depending on: their state, the state of other loads, the configuration of the system and on exogenous variables.

For example, in the case of the *"loads with states"* model proposed in *3.5*, where the probability of their operating load is conditioned to the state (e.g. or operative scenario), the unconditioned probability is obtained applying the law of the total probability. In fact, let $\mathrm{P}(P_{load}|S_i)$ be the operating load probability conditioned to the i^{th} scenarios S_i considered (e.g. of the total n possible scenarios).

Therefore, in order to calculate the probability of the operating load $\mathrm{P}(P_{load})$ unconditioned to the probability to be in a determined scenario $\mathrm{P}(S_i)$, it is required to apply the law of the total probability as proposed in equation *(60)*.

$$\mathrm{P}(P_{load}) = \sum_{i=0}^{n} \mathrm{P}(P_{load}|S_i) \cdot \mathrm{P}(S_i) \tag{60}$$

In this case, $\mathrm{P}(P_{load})$ represents the probability of a device to assume the value P_{load} for the operating load independently to the configuration, scenario or the state of other loads.

To allow a full understanding of this technique, a simple example is here proposed. In this case, in the specified ship operative scenario, the probability of a device to be on is equal to 60% (e.g. 0.6 in a probabilistic point of view).

Furthermore, the probability of the same device to assume a specified value of power absorbed (e.g. between a minimum and a maximum value) when this is on is described in Figure 29 by a triangular probability density function.

Therefore, applying the law of the total probability, it is possible to calculate the probability of the device to assume a certain operating load in that operative scenario (i.e. unconditioned to the state of the load), as proposed in Figure 30.

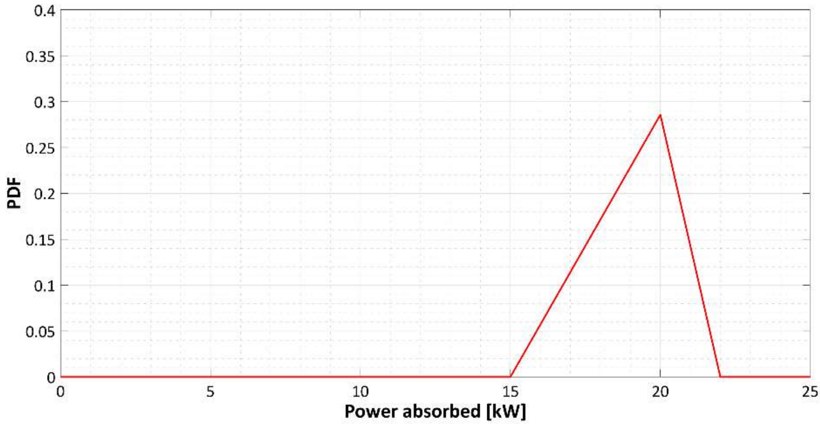


Figure 29 - Power absorbed by a device when this is on

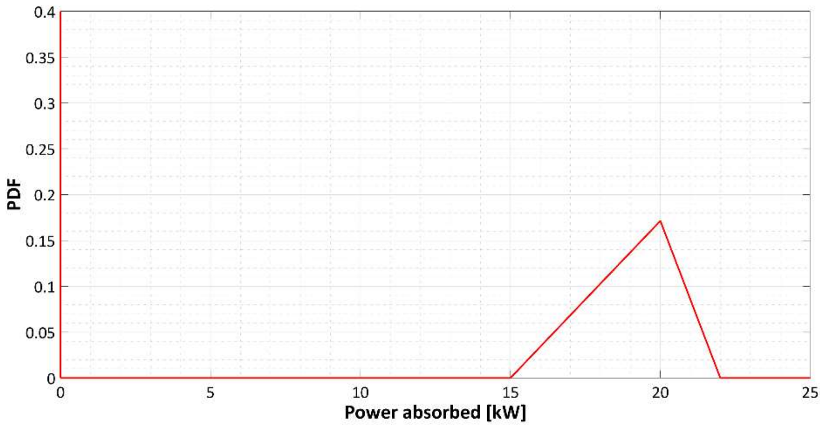


Figure 30 – Operating load of a device unconditioned to its state

This un-conditioning process can be performed before or during the statistical simulation without differences in the results yielded by the probabilistic approach to EPLA.

3.8 Methods of statistical simulation

In the previous paragraphs, probabilistic models for electric users have been formulated and proposed. To find analytic solutions to the system models simplifying assumptions and approximations are often required. In this context, numerical simulation methods are process involving the selection of a set of values of the system parameters in order to obtain a solution on the system model, considering the selected set.

By repeating the simulation process for several sets of system parameters, it is possible to obtain different sample solutions. A numerical simulation procedure applied to problems involving random variables with known or assumed probability distributions is called “statistical simulation” [89].

3.8.1 Monte Carlo simulation method

When the state of a system can be expressed by numerical variables, a first synthesis of the simulation can be stated by the arithmetic mean value of the states and their variance. This technique is named *“Monte Carlo”* to associate it not with gambling, but with the fact that in a gambling house, for example at the roulette table, the same random experiment is repeated under similar conditions a large number of times [90].

A distinction is sometimes made between simulation and Monte Carlo. In this view, simulation is a rather direct transcription into computing terms of a natural stochastic process. Monte Carlo, by contrast, is the solution by probabilistic methods of non-probabilistic problems [91]. Further, the Monte Carlo technique is sometimes called *“random approach”* due to its no chronological information retained during the sampling process.

In this context, it seems like it selects snapshot situations of the system, in contrast with a sequential approach, in which all the time steps are studied in their real chronological succession [92].

The Monte Carlo Simulation (MCS) approach to statistical simulation is here applied in order to evaluate the total operating load in each ship operative condition (or scenario) considered during the EPLA.

In this context, as shown in Figure 31, when performing a typical MCS process, the following steps are performed in order to achieve the final probability density function and cumulative distribution function:

- the main inputs should be prepared,
- the load characterization and distribution selection methods must be performed,
- each random variable and its probability density function and cumulative distribution function are considered as input of the MCS,
- the initial number of simulations and the expected error should be identified and set,
- a random process is performed, which selects a value for each random variable accordingly to its distribution. This is repeated for each simulation (or iteration),
- these values are summed in each simulation in order to evaluate the total operating load,
- therefore, the main statistical parameters are calculated and the error compared to the one selected at the beginning of the process.

In fact, if the calculated error is greater than the one selected a priori, the number of simulations is increased and the process updated, until the error will be lower than the reference one. Otherwise, the process is terminated and the probability distributions calculated.

In the MCS method, it is usually required that random variables are drawn from distributions (i.e. those identified in paragraph *3.6*) that defines the process. The process of *"sampling"* a value of the random variable *x* from its probability density function *f(x)*, as it is ordinarily called, is therefore an essential step in the MCS.

The main steps reported in Figure 31 are explained in details in the following sections.

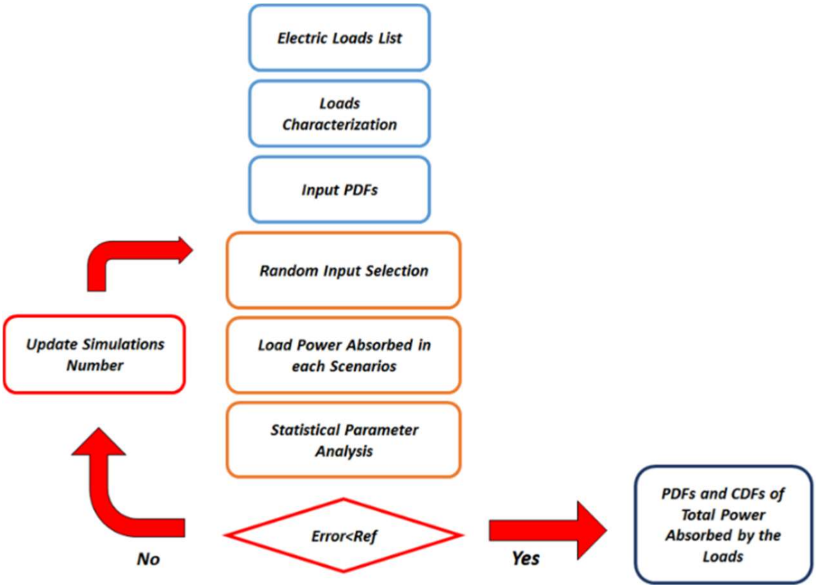


Figure 31 - MCS algorithm based on the probabilistic EPLA

- <u>Generation of random numbers</u>

Every MCs approach require the generation of random values appropriate in accordance with the distribution selected for each random variable (e.g. see paragraph *3.6*). Two possible approaches are available in order to perform this task [93]. The first one requires generating a uniformly distributed random number between 0 and 1.0. Then, through proper transformation technique, it is possible to obtain the corresponding random number with the correct probability distribution. The second one, on the other hand, consists in generating random values directly from a specific distribution applying the modern computing tools. However, due to the aim of this thesis and the characteristic of the probabilistic EPLA, only the first approach here reported is applied. In fact, it allows the use of different distribution and, in some particular cases, the adoption distributions not covered by the second one (e.g. many discrete distributions). For a given cumulative probability value *u*, it is possible to define the value of the variable *x* such that is valid *(61)*.

$$F(x) = u \tag{61}$$

The relationship between *u* and *x* is graphically proposed in Figure 32.

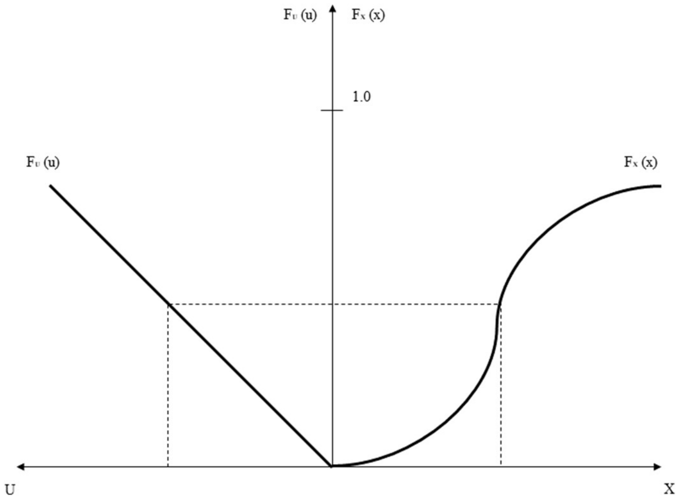


Figure 32 - Relation between u and x

Therefore, the value of the variable *X* is obtained by evaluating the *"inverse function"* reported in *(62)*.

$$x = F_X^{-1}(u) \tag{62}$$

In a MCS, this sampling process is repeated for each random variable for the total number of simulation *N,* identified at the beginning of the method.

- <u>Operating load evaluation</u>

Once the sampling process is finished, the MCS developed in this work performs the evaluation of the operating loads y_i associated to each sampling x_i (e.g. with $i=1, ..., M,$ where *M* is the total number of electric users considered). The total operating load (Y_j) in each ship operative condition is calculated by summing all the extractions preformed in the sampling phase for the operating load of each device y_i, as proposed in *(63)*.

$$Y_j = \sum_{i=1}^{M} y_{ij} \tag{63}$$

This, is performed for each i^{th} simulation. Then the main statistical parameters for the total operating load in each ship operative conditions can be evaluated. These parameters, such as the mean and variance, are useful to evaluate the accuracy of the MCS.

- <u>Accuracy of the MCS</u>

In a sampling experiment, the accuracy of results increase with the number of samples. Therefore, the accuracy of the MCS depends on the number of simulations (or iterations) preformed. From what proposed in [94], it is possible to note that the error in the estimation of the mean is inversely proportional to the square root of N (total number of simulations). Consequently, to improve the estimation by a factor of 2, it is required to increase the sample size of 4. In other studies, the number of simulation required to achieve a certain accuracy has been presented [95]. In this work, the formulation proposed in equations *(64)* and *(65)* are adopted in order to evaluate the percentage error of the MCS and the number of simulations required to achieve the desired accuracy, respectively.

$$E = \frac{3\sigma_x}{\mu\sqrt{n}} \tag{64}$$

$$N = \left[\frac{3\sigma_x}{\mu E}\right]^2 \tag{65}$$

Therefore, if the error E is not satisfied by the first number of iterations stated at the beginning of the MCS, it is required to update their number N as proposed in *(65)* and shown in Figure 31.

- <u>Outputs evaluation</u>

Considering the probabilistic EPLA, the outputs from the MCS are the probability density function and cumulative distribution function for the total operating load (e.g. as proposed in Figure 31), considering each ship operative scenario. Furthermore, interesting outcomes are also the statistical parameters, such as mean and variance, of these distributions.

An applicative example of how the MCS can be applied to the probabilistic EPLA, and its results, is proposed in paragraph *3.12* of this thesis.

In conclusion to the statistical simulation method, it is possible to highlight that, result of this method are the probability and cumulative density function for the total operating load in each ship operative conditions. However, as it happened in paragraph *3.7*, the operating load variables are conditioned to the probability of occurrence of each scenario considered. Therefore, in order to overcome these conditions and calculate the total operating load un-conditioned to the probability of each scenario, the un-conditioning criterion proposed in *3.7* will be applied to this case in the following paragraph.

3.9 Unconditioned total operating load

Considering the outputs probability density functions and cumulative distribution functions obtained applying the statistical simulation methods proposed in *3.8*, it would be useful, in a power generation system sizing perspective, to evaluate the total operating load for the shipboard power system unconditioned to the probability of occurrence of each operative scenario. The un-conditioning technique has already been introduced in this thesis in paragraph *3.7*. Accordingly to this definition, the total operating load random variables are here subject to the *"total probability theorem"* proposed in *(59)*.

A detailed applicative example of the results obtained is proposed in paragraph *3.11*, where the probabilistic approach formulated in this thesis is applied to two case studies. The total operating load unconditioned is a useful information in order to evaluate the power demanded, perform average fuel oil consumption calculations and risk assessment.

Finally, the un-conditioning procedure applied to the total operating load is essential in order to perform long-term peaks forecasting and extreme values prediction

3.10 Introduction to a probabilistic risk assessment

Implicit, but not already discussed is the risk associated with the sizing of the power generation system as result of the power demand evaluated by the probabilistic EPLA. In fact, until the ship actually experiences the entire operative and ambient conditions for which it was designed, persist the risk that the power system (e.g. considering the power generation, transmission and distribution systems) has not been sized properly.

Typical risk assessment considers both the probability and the effect of a failure to evaluate the associated risk for the ship. In this perspective, it has been assumed that a very low risk should be adopted in design phase. However, it is to be noted that, cost, size, and time are driving industry and shipyards to size the system with more risk [48]. This is even more emphasized when a traditional method to perform an EPLA is applied. In fact, being the result of such a method merely a number, it is even more difficult to perform a risk analysis without applying large safety margins in order to reduce the risk associated to a design configuration.

On the other hand, applying a probabilistic approach to EPLA, a more detailed risk analysis is possible. In fact, probabilities are associated to each value of the total operating load and power demand. This allows the designer to consider which level of risk associated to a certain design configuration is acceptable (e.g. instead of apply safety margins).

A probabilistic risk analysis (PRA) involves the following main steps [103]-[108]:

- the identification of the potential events of failures and their modes of failures,

- estimation of the consequences of these failures on the total system,
- estimation of the probability of occurrence of each event of failure,
- comparison of the results of the analysis against an acceptability criterion or criteria.

In this context, in Table 13 an example of the probability associated with a failure depending on the power generation sizing is proposed. In fact, Table 13 proposes both the sigma levels (e.g. the standard deviation value associated to a random variable probability) associated to the percent of power load and the number of hours per year that the load is not covered by the generation. Essentially, it reports the corresponding hours per year not covered by the power generation system, if this is designed with a specified sigma level of load.

TABLE 13 – SIGMA, PERCENTAGE OF TOTAL OPERATING LOAD AND HOURS PER ANNUM NOT COVERED BY A POWER GENERATION SYSTEM OF A BULK CARRIER SHIP

Sigma	**% Total Operating Load**	**Hours per year**
1	31	6044
2	69.1	2702
3	93.3	585
4	99.37	54.4
5	99.97	2.04
6	99.9997	0.03

Table 13 shows that a 6-sigma approach would address to 99.9997% of the total operating load, allowing only 1.8 minutes of overload per year. On the other hand, a 4-sigma approach would address to 99.0% of the total operating load corresponding to 14.4 minutes per day not covered by the generation system. This gap in power can be managed adopting strategies such as load shedding or load shifting, which allow preventing the system from dangerous blackout conditions.

3.11 Case studies

In the previous paragraphs, the probabilistic approach to EPLA has been formulated. Methods to load characterization, statistic characterization of the random variables and statistical simulation have been proposed based on both the information available and the design phase of the ship.

On the other hand, in this paragraph, this approach to EPLA has been developed and validated applying the probabilistic methodology to two case studies, a bulk carrier and a large cruise vessel.

It should be noted that experimental readings are available thanks to a measurement campaign conducted on board a naval vessel. However, being the aim of this measurement campaign just a monitoring on some users, the probabilistic approach to EPLA has not been tested on this vessel. For this reason, in order to validate this approach, this formulation has been applied to two merchant ships, with present different power system configuration.

In the following, the problem is stated in order to introduce the methodology applied to the case studies, considering the methods proposed and the information available. In fact, due to a lack of experimental readings for the two case studies, methods based on measurements for the statistical characterization of the random variables have not been adopted.

In order to allow a comparison between the deterministic approach and the probabilistic one, the former will also be performed for the two case studies and its result presented. Finally, a sensitivity analysis on the different distributions selected to characterize each random variable, performed on the bulk carrier ship, is presented and analysed.

3.11.1 Bulk carrier description

In the second half of the 20th Century, the volume of cargoes transported by sea in bulk increased quickly, leading to specialist ships. These, were ships carrying cargoes, which did not demand packaging and which could benefit from the economies of scale. Traditional bulk carriers are single deck ships that present a longitudinally framed and a double bottom, with the cargo-carrying section of the ship divided into holds. The hold arrangements can vary according to the range of cargoes to be carried. Framing is contained within the double bottom and wing tanks to leave the inner surfaces of the holds smooth. These ships can be categorized as [13]:

- *Panamax*, where the dimensions of the ship are limited by the need to be able to transit the Panama Canal. Therefore, the beam must be less than 32.25 m.
- *Suezmax*, where the draught must be less than 19 m.
- *Capesize*, which does not have the restrictions of the above types.
- *Handysize*, which are generally less than about 50000 tonnes.
- *Aframax*, for tankers in the range 80000–120000 dwt.

Dry bulk carriers ships carry bulk cargoes such as coal, grain, bauxite, iron ore, phosphate and nitrate. Apart from saving the costs of packaging, loading and off-loading times are reduced. As the volume of cargo carried increased so did the size of ship, taking advantage of improving technology.

To improve the safety of these ships IMO promoting a series of measures during the 1990s, which reflect lessons learned from the losses of ships in the early 1990s. A formal safety assessment was carried out to guide future decisions on safety matters for bulk carriers. For example, in a general-purpose bulk carrier, as the one proposed in Figure 33, only the central section of the hold is used for cargo and the partitioned tanks that surround the hold are used only for ballast purposes. This hold shape also results in a self-trimming cargo. During unloading the bulk cargo falls into the space below the hatchway facilitating the use of grabs or other mechanical unloaders [13].

The bulk carrier under exam presents the main characteristics summarized in Table 14. The most important information are those concerning the total power installed for generation. In this case, three diesel generators of 720 kW are installed.

TABLE 14 - BULK CARRIER SHIP MAIN CHARAXCTERISTICS

Parameters	Value	Measure
L_{OA} (Length Over All)	180	m
B (Breath)	30	m
T (Draft)	10.2	m
DWT (Dead weight Tonnage)	34000	t
V_{SHIP}	15	kn
Main Engine (propulsion)	9000	kW
Diesel Generators	3 x 720	kW

As previously stated in this chapter, core input to EPLA is a complete list of the electric devices installed on board the ship. This list, due to reasons of comprehensibility of this paragraph, is proposed in its full version in Table B-I of Appendix B.

Moreover, other important information such as the rated power of each device and the deterministic factors applied to each device to perform a deterministic approach to EPLA are also proposed in in Table B-I of Appendix B.

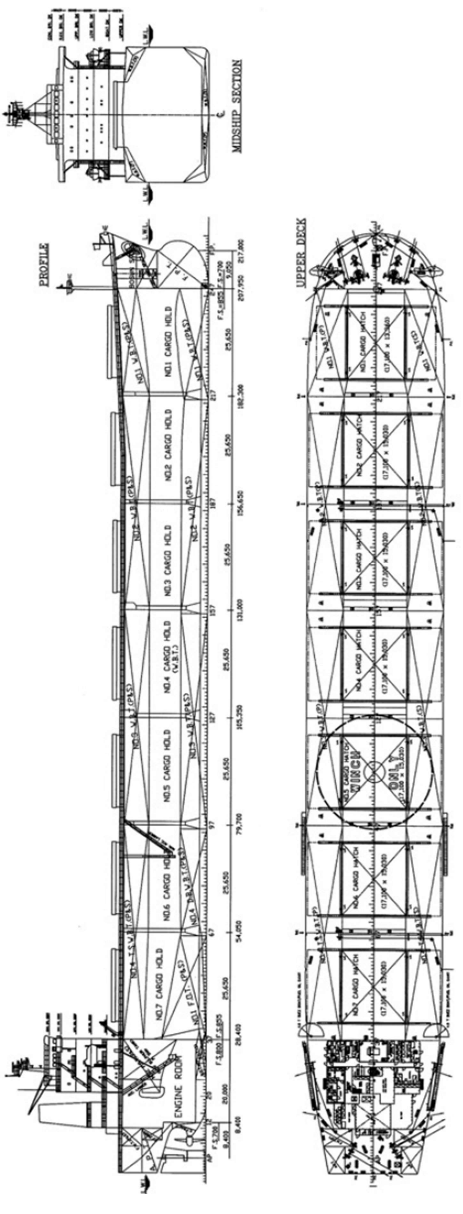


Figure 33 - General purpose bulk carrier ship, courtesy of RINA in [13]

3.11.2 Large cruise vessel description

Passenger ships can be divided in two categories, the cruise ship and the ferry. Ferries provide a link in a transport system and often has roll on roll off (Ro-Ro) facilities in addition to its passengers. On the other hand, cruise ship (e.g. proposed in Figure 34) carries only passengers around a certain route within a limited time, which usually is a multiple of one week.

Between 1990 and 2000, the cruise market grew by 60% and the size of ship has grown with vessels now capable of carrying 3600 passengers at 22 knots [13]. However, largest cruise ships can not use some ports and harbours in the more attractive locations. In fact, the ship has to anchor well out and ferry passengers ashore by smaller boats.

It should be noted that, in a cruise ship, passengers are provided with a very high standard of accommodation and leisure facilities. This results in a large superstructure as a prominent feature of the vessel and a high level of power required by the on-board users. In fact, often this kind of ship presents a generation power installed comparable to small cities (e.g. several tens of MW installed).

Recently, these ships present an integrated electric power system, where all the main users, and especially those related to the propulsion, are powered by electricity. In this perspective, it is possible to state that, large cruise ships are the closest to the concept of AES introduced in Chapter 1 of this thesis. For this case study, the power system configuration schema is available and shown in Figure 35.

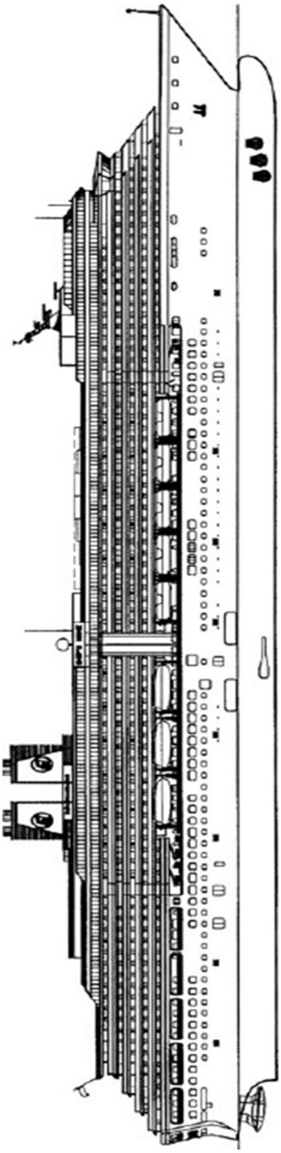


Figure 34 - Typical large cruise ship, courtesy of RINA in [13]

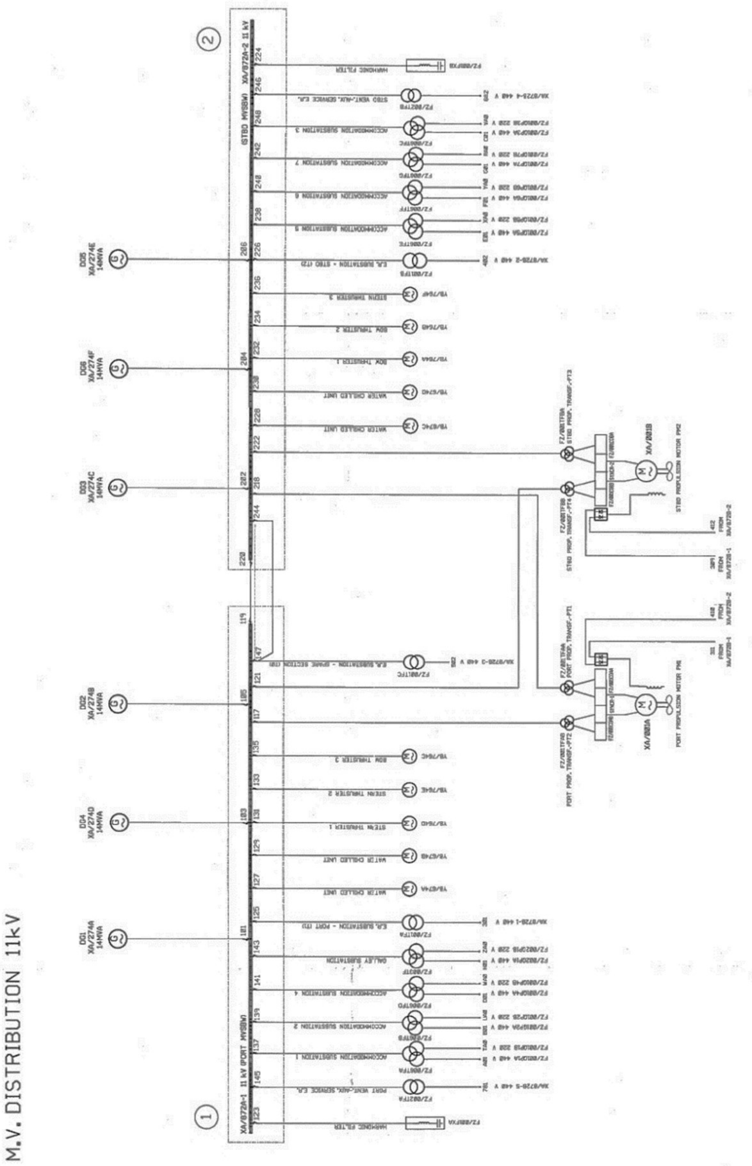


Figure 35 - Cruise vessel power system layout

The main characteristics of the second case study are summarized in Table 15.

TABLE 15 – LARGE CRUISE SHIP MAIN CHARACTERISTICS

Parameters	Value	Measure
L_{OA} (Length Over All)	290	m
B (Breath)	32.25	m
T (Draft)	8.3	m
Gross Tonnage	110000	GRT
V_{SHIP}	21	kn
Propulsion Load	42	MW
Diesel Generators	6 x 12.6	MW

Further, also for this case study, core information such as the complete list of the electric devices installed, their rated power and deterministic factors applied to perform the deterministic EPLA are reported in in Table B-II of Appendix B of this thesis.

3.11.3 Deterministic EPLA applied to the bulk carrier ship

In order to allow a comparison of the results yielded by the deterministic and probabilistic approaches to EPLA, the former method is here applied to the bulk carries ship.

The deterministic EPLA is performed for major load categories, such as propulsion, propulsion auxiliaries, HVAC system, lighting, emergency lighting, navigation, deck machinery and hotel. The categories are subjected to different percentage loading requirements (e.g. called load factor) to support different loads. Some loads are to be considered at a 100 percent load factor, some others are to be considered for less than 100 percent load factors; finally, there are loads with zero load factors operating conditions.

The number of generators and their ratings depend on the maximum demand load for the system set-up, such as full speed propulsion, anchor operation, shore side operation etc. The total demand load is the factored load calculated for the different operating requirements and the highest load demand calculated is considered as the total demand load for the power generation.

If there is a requirement of additional load margin on certain categories, that growth margin should be added to the calculated maximum to determine the power generation requirement [40]. Therefore, for EPLA it is necessary to identify all electric power-consuming devices, and to understand the operating characteristics of those devices. The power consumption demand varies from one operating condition to another condition for the same equipment.

Input information have been reported in in Table B-I of Appendix B. The list of loads reports useful information, different depending on the user under consideration. Users such as pumps are characterized by their values of flow rate and hydraulic head as in *(66)*.

$$P_{absorbed} = \frac{Q_{pump} \cdot H}{\eta \cdot 3.6} \tag{66}$$

Where $P_{absorbed}$ is the power absorbed by the electrical motor of the pump Q_{pump} is the pump massive flow rate (e.g. expressed in m3/h), H is the total pump pressure head (e.g. expressed in MPa) and, finally, η is the efficiency factor for the pump.

The corresponding nominal power of the electrical motor is calculate as proposed in *(67)*.

$$P_N = \frac{P_{absorbed}}{\eta_{em}} \tag{67}$$

Where, P_N is the value of the nominal power of the electrical motor and η_{em} is the efficiency factor of the electrical motor.

For other rotating loads such as engines, compressors and other types of pump, manufacturers give the nominal power. The load list reports other information about the number of installed items for each user. For each operative ship scenario, the number of devices switched on are reported with the corresponding required power.

The deterministic approach here applied is the one based on the use of *load factors*, already introduced in Chapter 2 of this thesis. The main operative conditions considered to perform this task are:

- *Anchor,* which is an operative condition where the ship is in port or at anchor, with all the power required by the on board electric users supplied by the power system. Propulsion loads are switched off but some auxiliaries are still online (e.g. such as the low temperature cooling system).
- *Manoeuvring,* is one of the most severe and dangerous operative conditions for every ship. In fact, in this condition the ship must be able to manoeuvring, often in restricted and shallowed water, in safety adopting its propellers and thrusters.
- *Cruising,* ships are designed for this operative scenario. Here the ship is cruising at sea subject to different weather conditions adopting its propulsion system. Bulk carrier ships present, traditionally, only one cruising speed in which they are designed. In such a condition, all the auxiliaries to propulsion are online.
- *Loading/Unloading,* a bulk carrier is built for this condition, where the goods are loaded or unloaded from the holds. Often, cranes are installed on the main deck of these ships to allow the movement of the payload in ports where the infrastructures are limited. For this reason, high loads are present in this condition (i.e. due to cranes), which is the most severe in a power system perspective for the case study ship.

The load factors applied for each user can varies depending on the operative condition considered. Therefore, in order to simplify the process, loads are divided depending on the service supplied. In this context, the state of the art is to use unique system sequence numbers called Ship Work Breakdown Sequence (SWBS). This provides a structured sequenced number for shipboard systems and sub-systems, such as SWBS 304 for electric cables. The SWBS numbers are also used in commercial shipbuilding as well, the main ship systems are divided as follow:

- 200-299 Propulsion plant system,
- 300-399 Electric plant system,
- 400-499 Command and Surveillance,
- 500-599 Auxiliary system,
- 600-699 Outfit and Furnishings,
- 700-799 Combat system.

The previous list starts numbering from 200 because the numbers from zero to 199 are dedicated to general guidance and hull structures, which are not of interest in this context.

Once all the required information have been identified and the load factors assigned to each load in each ship operative scenario, the EPLA's calculation can be performed and the results obtained.

Finally, the main results for the bulk carrier (e.g. total operating load in each scenario) are proposed in Table 16.

TABLE 16 - RESULTS YIELDED BY APPLYING THE DETERMINISTIC EPLA TO THE BULK CARRIER SHIP

	In Port	**Man.**	**Cruising**	**Loading-Unloading**
Total operating load [kW]	433	724	610	1068

3.11.4 Deterministic EPLA applied to the large cruise vessel

Concerning the cruise vessel, the same approach to the traditional EPLA applied to the bulk carrier has been performed (e.g. based on load factors). However, due to the different purpose of this ship compared to the bulk carrier one, the *Loading/unloading* condition is not considered. On the other hand, in this case, three cruising conditions are selected (e.g. at 10, 20 kn and full speed).

It should be noted that, being an IES, the cruise is an electric propulsive ship, where all the power required for the propulsion is delivered by the power system. Therefore, both in the deterministic and probabilistic approaches to EPLA, also this power demand must be considered and modeled, differently form the bulk carrier ship.

The main result obtained by the deterministic EPLA applied to the cruise are summarized in Table 17. It is possible to highlight that, for this case study, the propulsive load is the highest one (e.g. more than 44 MW in cruising at full speed). Moreover, except in manoeuvring condition, the non-propulsive load is slightly constant (e.g. close to 18 MW) in each scenario.

This, probably, is due to the constant services and comforts that this kind of ships must supply to the customers, independently from the scenario considered. In manoeuvring, on the other hand, the increase in non-propulsive load is mainly due to the power required for mooring system (as shown in Table B-II of Appendix B).

TABLE 17 – RESULTS YIELDED BY APPLYING THE DETERMINISTIC EPLA TO THE LARGE CRUISE VESSEL

	Shore	**Man.**	**Cruising 10kn**	**Cruising 20kn**	**Cruising Max**
Total operating load [MW]	17.9	33.2	31.3	43.1	62.8
Propulsive load [MW]	0	8.4	12.9	24.6	44.4
Non-propulsive loads [MW]	17.9	24.8	18.4	18.5	18.4

3.11.5 Probabilistic approach, problem statement and sensibility analysis

The probabilistic approach to EPLA applied to test the methodology is mainly affected on the information available on the two case studies. In this context, very different information are available for the two case studies. Information on the bulk carrier are a complete list of the electric users installed on board the ship, their rated power and the load factors applied during the deterministic EPLA.

On the other hand, for the cruise one, in addition to the same information listed for the bulk carrier, detailed information about each device are available by the manufacturer and the shipyard manuals. However, in both the cases experimental readings are not available; therefore, the stochastic characterization of the random variables proposed in paragraph *3.6* will be based on the *"based on knowledge"* approach already described.

However, in order to test the sensitivity of this method to changes into the input in formation (e.g. the distributions selected to characterize each random variable), a sensitivity analysis has been performed and the results are here proposed. The four distributions applied for this analysis are:

- the Bernouilli's distribution,
- the discrete distribution,
- the uniform distribution,
- the triangular distribution.

In this context, the sensitivity analysis considers four simulation cases. In each case, the random variables that describe a load are characterized adopting one of the previous distributions. The random variables selected in order to characterize each load, in a probabilistic perspective, are the same in each simulation in order to allow a comparison between the simulations.

Comparing the results obtained applying each distribution to characterize the random variables, four probability density functions and cumulative distribution functions for the total operating load unconditioned have been obtained, as proposed in Figure 36 and Figure 37.

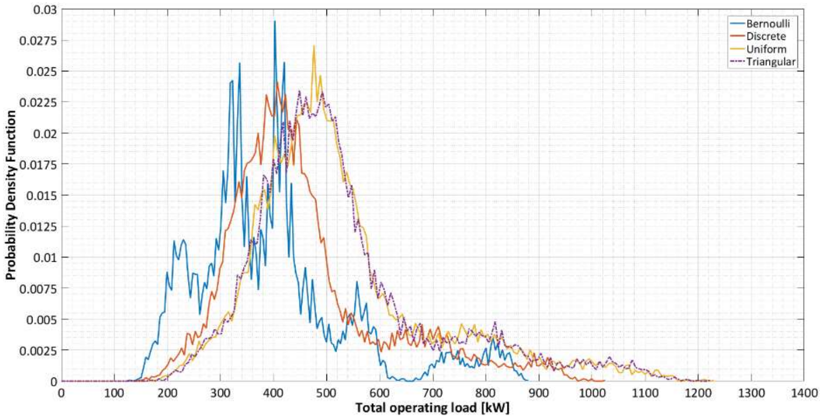


Figure 36 - PDFs for the total operating load unconditioned resulting from the sensitivity analysis

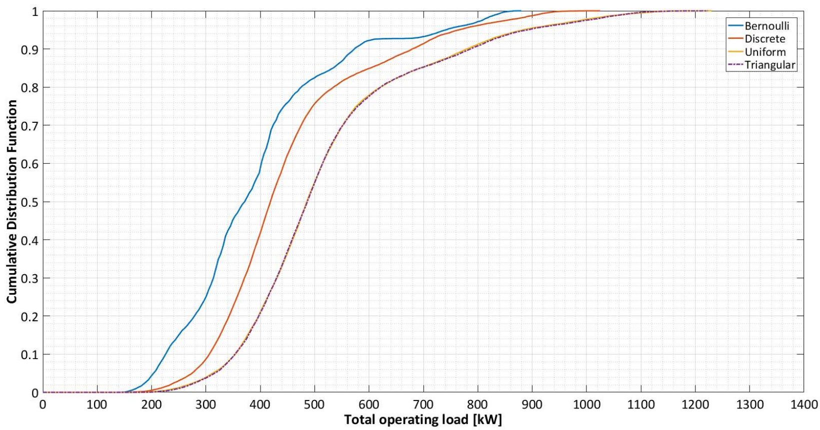


Figure 37 - CDFs for the total operating load unconditioned resulting from the sensitivity analysis

The results obtained in each simulation (i.e. one simulation for each distribution), considering each operating condition (e.g. anchor, manoeuvring, cruising and loading/unloading) are summarized in Table 18.

Therefore, it is possible to highlight that, the minimum total operating load is identified (i.e. the minimum values for the statistical mean and percentile 95) applying the Bernoulli distribution to each random variable.

Moreover, adopting respectively the discrete, uniform and triangular distribution, these statistical values increase significantly. This is mainly due to the *"dispersion effect"* of the load power adopting the uniform and triangular distributions, especially.

Finally, from the results proposed in Figure 37, a similar behaviour for the uniform and triangular distributions is pointed out (e.g. in yellow and violet, respectively).

TABLE 18 - MAIN RESULTS OF THE SENSIBILITY ANALYSIS ON THE DISTRIBUTION SELECTION

Parameters	**Bernoulli**	**Discrete**	**Uniform**	**Triangular**
Mean	367	417,1	482	485,6
Maximum	879,8	1024,7	1229,7	1223,2
Percentile (95)	738,3	762,1	877,5	885,2
STD	149,2	150,8	176	176,3

3.11.6 Probabilistic EPLA for the bulk carrier ship

Considering the algorithm proposed in Figure 7 for the probabilistic EPLA, once the input information have been identified, it is required to characterize each load (e.g. selecting which random variables can describe their operating load). Therefore, in in Table B-I of Appendix B, the characterization model adopted for each load is proposed in detail. Moreover, to allow a better understanding of how this test has been performed, some examples on these models are here reported and explained.

- Constant load model

As proposed in *3.5.1*, constant loads may be described by a single random variable. Whether the state (e.g. on or off) of the user under exam is always on, this single random variable can identifies the amount of operating load of this user. On the other hand, when this user shows a constant operating load behaviour, this random variable describes the varying state of the user.
This is the case of the lighting system. In fact, this system, when it is on, presents a constant power absorbed.

Nevertheless, this value depends also on the number of bulbs switched on. Therefore, it can be modeled with a single variable, which identifies its operating load. However, the statistical characterization of this load must take into consideration the different probability associated to the number of bulbs on in each scenario. Therefore, a discrete distribution function has been selected in order to model the power absorbed by these system (e.g. as it has been shown previously in Figure 10). Other loads that have been characterized with a similar model are the resistive loads for heating/pre-heating purposed of machinery systems (e.g. as proposed in Figure 8).

It should be noted that, the random variable *"state of the load"* has always been modeled with a discrete Bernoulli distribution, for each model presented in this thesis.

- Loads with operating states

Differently from the constant loads, the loads with states shown a behaviour that is affected by both the state and the power absorbed of the user exanimated (i.e. both these variables are varying in time). It means that, these loads are characterized at least by two random variables (i.e. state and power absorbed), which present a discrete Bernoulli distribution for the state and another distribution for the power absorbed (e.g. discrete distribution function).

A communication system, for example, can be characterized with this model. In this context, its power absorbed depends on the operative condition of the ship and on the necessity. Therefore, a discrete distribution can be selected to model the power absorbed by this system.

- <u>Continuous variable loads</u>

A continuous variable load presents a time-varying behaviour of its operating load. This may depends on both the state and the power absorbed by the user. The state is characterized with a random variable described by the usual Bernoulli distribution. The power absorbed, on the other hand, can be modeled applying a continuous distribution function (e.g. uniform, triangular or normal). Several pumps, compressors and engines are characterized with this model. The crane system, which is of mainly importance for the bulk carrier, has been characterized with this model. In fact, it depends on the weight of the goods it moves and on the operative conditions (e.g. also on the environmental forces applied on the crane). Consequently, it shows a continuous variable load over the time.

- <u>MCS parameters setting</u>

To perform the MCS adopting the identified random variables, some parameters have to be set:

- firstly, the accuracy of the simulation must be selected. For the test here proposed, an accuracy equal to the 95% has been selected, i.e. an error E equal to 5% is allowed (e.g. based on the obtained standard deviation), as formulated in equation *(64)*.
- Secondly, the number of initial iterations (simulations) performed by the MCS in the first loop, must be defined. To validate the proposed method, this value has been set equal to 5000 iterations.
- The probability of each operative scenarios should be defined; otherwise, the same probability of occurrence would be selected automatically for each one. In this validation test, the probabilities have been set equal to 53, 2, 13 and 32 percent for the cruising, manoeuvring, anchor and loading/unloading conditions, respectively.

Once each parameter has been defined, the MCS can be performed. The main results yielded by this test are proposed in the following.

- <u>Results for the bulk carrier ship</u>

Probability density functions and cumulative distribution functions are the main results of the proposed approach to EPLA. These PDF and CDF have the objective to describe the total operating load of the power system under exam in each operative scenario that has been considered.

Differently from the deterministic approach to EPLA, the results proposed for the probabilistic approach must be interpreted appropriately. In fact, a wide range of values of operating load is proposed in each PDF and CDF. Therefore, the first question to be answered is *"which value can be compared to the deterministic result?"*. The answer to this question depends on the objective of the EPLA (e.g. sizing the generation, sizing the distribution system, perform fuel oil consumption endurance calculation, risk assessment and so on, as proposed in Figure 2).

In the perspective of sizing the generation system (e.g. diesel generators), the mean values (or modal values) obtained for each operative condition and the percentile 95 (or 99) of the total operating load unconditioned are the main parameters that can be compared with the results yielded by the deterministic approach. In the following figures the result obtained for the case study are proposed and analysed.

In Figure 38, the results obtained for the *anchor* scenario are proposed. Here, it is possible to highlight that, a modal value close to 350 kW exists and the mean value is close to 430 kW. Furthermore, the percentile 95 and maximum values are equal to 880 kW and 640 kW, respectively.

Comparing these results to those obtained applying the deterministic approach (i.e. a total operating load equal to 610 kW), a reduction close to 200 kW is pointed out.

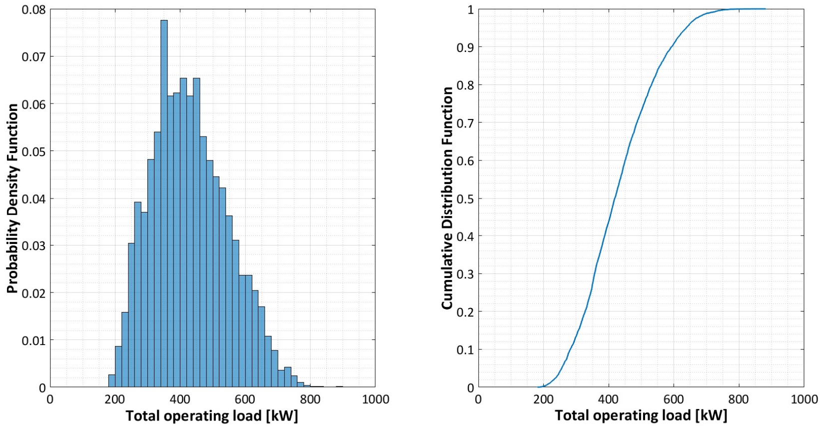


Figure 38 - Total operating load PDF and CDF in anchor condition for the bulk carrier

Considering the *manoeuvring* condition, in Figure 39 are proposed the distribution functions for the total operating load.

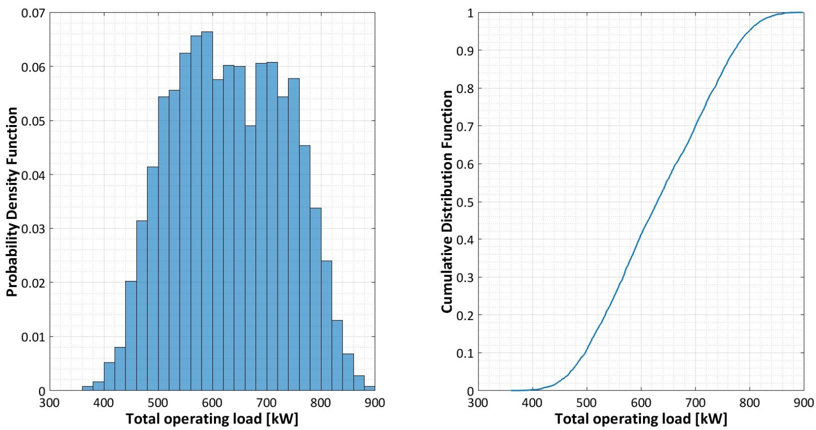


Figure 39 - Total operating load PDF and CDF in anchor condition for the bulk carrier

These distribution functions show a behaviour that is quite similar to a uniform distribution, between a minimum and a maximum values close to 400 kW and 900 kW, respectively. However, the mean value, in this scenario, is equal to 630 kW. A reduction close to 100 kW, compared to the deterministic approach, is highlighted. The percentile 95 is here equal to 800 kW, close to the value obtained in the deterministic approach.

Concerning the *cruising* operative condition, the main results are proposed in Figure 40. In this condition, the mean, maximum and percentile values are equal to 430 kW, 640 kW and 530 kW, respectively.

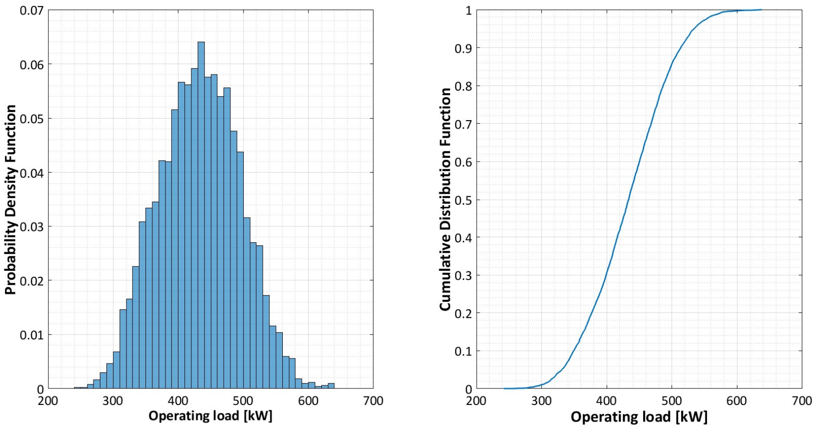


Figure 40 - Total operating load PDF and CDF in cruising condition for the bulk carrier

Compared to the deterministic approach to EPLA, the probabilistic one shows a reduction in the total operating load of the system equal to 180 kW. The results obtained for the last operative scenario, the *loading/unloading* one, are proposed in Figure 41. In this case, a bimodal distribution function has been obtained. These modal values are close to 500 kW and 750 kW. However, points of increased density of probability are also close to 300 kW and 1000 kW. The mean, maximum and percentile 95 values are here equal to 632 kW, 1135 kW and 990 kW, respectively. This corresponds to a reduction close to 400 kW compared to the deterministic approach.

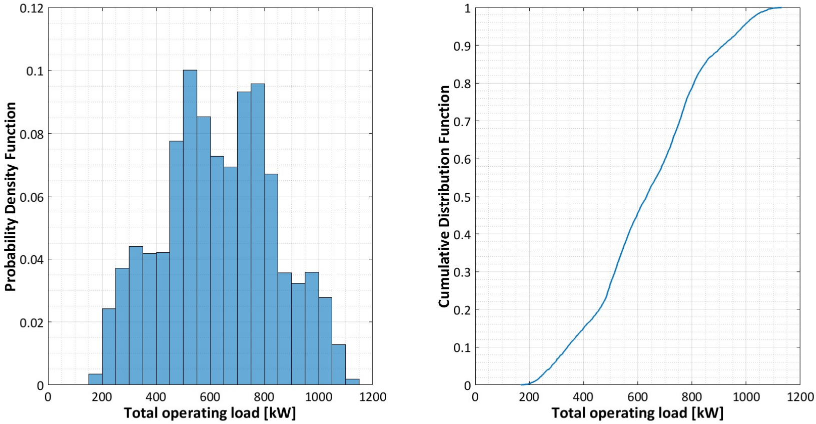


Figure 41 - Total operating load PDF and CDF in loading/unloading condition for the bulk carrier

Once these PDF and CDF have been obtained and the probability of occurrence of each scenario defined, it would be possible to evaluate the total operative load unconditioned to the operative conditions. In Figure 42, the distribution functions, calculated applying the theorem of the total probability, are proposed.

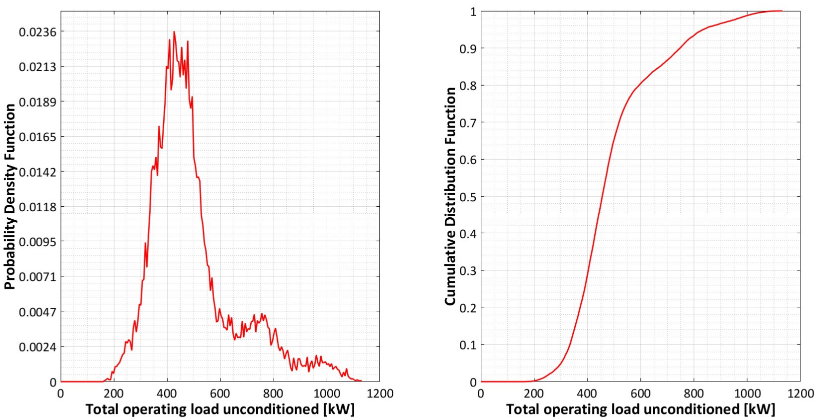


Figure 42 - Total operating load unconditioned PDF and CDF for the bulk carrier

In this context, a mean, maximum and percentile 95 values equal to 455 kW, 1130 kW and 830 kW, have been respectively obtained. Three modal values close to 450 kW, 750 kW and 950 kW are highlighted. Therefore, in order to prevent from the risk of under sizing the generation system, a risk assessment should be performed (as proposed in paragraph *3.10),* based on these unconditioned distributions. In Table 19, a *sigma* analysis for the case study is proposed in order to allow a complete understanding of this methodology.

TABLE 19 - SIGMA APPROACH FOR RISK ASSESSMENT CONSIDERING THE TOTAL OPERATING LOAD UNCONDITIONED, FOR THE BULK CARRIER SHIP

Sigma	**% Total Operating Load**	**Hours per year**
1	82.2	1562
2	93.2	597
3	98.0	174
4	100	0

This analysis shows that a 3-sigma approach would address to 28 minutes per day not covered by the generation, which can be managed by the on board automation system in order to prevent from dangerous blackout conditions. Another reasonable value for the sizing of the power generation system can be the percentile 99 of the total operating load unconditioned. For this case study, this value is equal to 1050 kW. Therefore, the total power installed for the power generation should be greater equal to this percentile 99 value (e.g. without considering fault scenarios, as required by the normative [109]).

3.11.7 Probabilistic EPLA for the large cruise vessel

As reported for the bulk carrier ship, also for the large cruise vessel here under exam, in in Table B-II of Appendix B, the characterization model adopted for each load is proposed in detail. Examples to this load characterization have already been proposed in paragraph *3.11.6*, for the bulk carrier.

Parameters for the MCS have been set equal to those proposed in the previous case study. The total number of simulations performed is equal to the initial 5000 iterations defined as input to the MCS. The probability of occurrence of each ship operative condition are 0.21, 0.0208, 0.2628, 0.3956 and 0.1109 for the anchor, manoeuvring, cruising at 10 kn, cruising at 20 kn and cruising at maximum speed scenarios, respectively [9]. The results obtained applying the probabilistic approach to the large cruise vessel are here proposed.

Considering the *anchor* operative condition, Figure 43 shows the probabilistic behaviour for the total operating load in this condition. It is possible to note that, the minimum, mean, maximum, and percentile 95 values are equal to 3.7 MW, 7.96 MW, 14.9 MW and 9.6 MW, respectively.

Furthermore, the modal value is close to 7.5 MW in this operative condition. Being the cruise under exam a n electric propulsive ship, in anchor condition, the propulsive load is equal to 0. However, some auxiliaries to the propulsion system are in function (e.g. cooling system). Comparing the mean value obtained applying the probabilistic approach to EPLA with the result obtained applying the deterministic one, a reduction close to 10 MW is found.

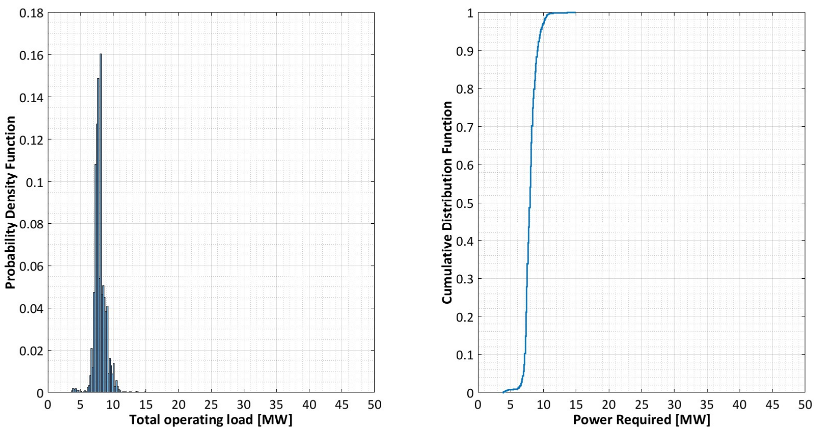


Figure 43 - Total operating load PDF and CDF in anchor condition for the cruise vessel

In *manoeuvring* condition, as proposed in Figure 44, the modal value is close to 10 MW. Moreover, the other statistical parameters of interest are the minimum, mean, maximum and percentile 95, equal to 5.3 MW, 9.7 MW, 20.3 MW and 15.1 MW, respectively.

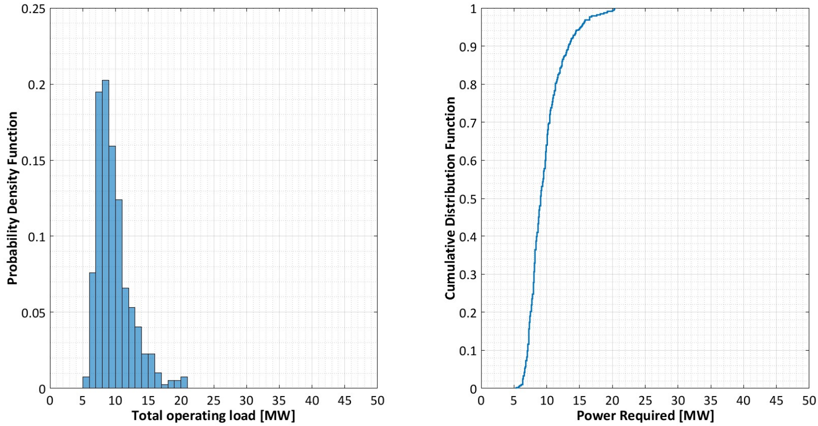


Figure 44 - Total operating load PDF and CDF in manoeuvring condition for the cruise vessel

Compared to the 33.2 MW evaluated applying the deterministic approach to EPLA, a sensible reduction is highlighted (e.g. comparing the deterministic result to the mean value here proposed, the difference is close to 20 MW). Analysing the *cruising at 10kn* scenario, which behaviour is proposed in Figure 45, a significate peak in the probability density function close to 16 MW is pointed out. This peak is mainly due to the propulsive load. Moreover, the minimum, mean, maximum and percentile 95 values are equal to 6.8 MW, 15.8 MW, 29 MW and 18 MW, correspondingly. In this case, a reduction in the total operating load close to 15 MW is pointed out. Compared to the probability function obtained for the anchor condition, in this case a wider range of possible loading condition has been found. In fact, traditionally, the manoeuvring condition is one of the most critical operative condition (e.g. often having to manoeuvre in narrow waters). For this reason, the propulsive motors are all online, although at low load and, as a result, the power absorbed by the auxiliaries in this scenario is more significant than in the others.

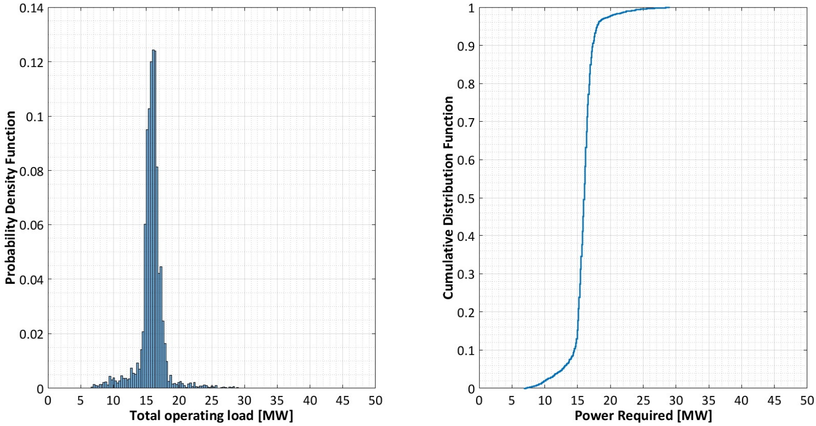


Figure 45 - Total operating load PDF and CDF in cruising 10 kn condition for the cruise vessel

Furthermore, considering the total operating load (proposed in Figure 46) at *cruising 20 kn* operative condition, a modal value equal to 29 MW is shown.

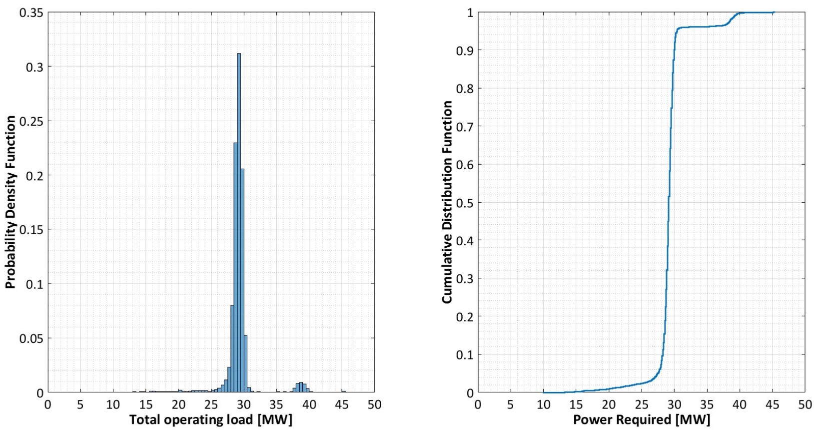


Figure 46 - Total operating load PDF and CDF in cruising 20 kn condition for the cruise vessel

In addition, a second modal value (e.g. with a probability of occurrence significate lower than the former one) is highlighted at 38 MW.

Summarizing the main statistical parameters, the minimum, mean, maximum and percentile 95 values are equal to 9.9 MW, 29.2 MW, 45.3 MW and 30.4 MW, respectively. The reduction in the total operating load obtained applying the probabilistic approach, rather than the deterministic one, is close to 13 MW.

Finally, the *cruising at maximum speed* scenario presents several points of significate density of probability (e.g. as shown in Figure 47); however, the highest one is close to 38 MW. From the results yielded applying the probabilistic approach to EPLA to the case study under exam, the statistical parameters: minimum, mean, maximum and percentile 95 values are equal to 25.4 MW, 38.6 MW, 48.5 MW and 43MW, respectively. Therefore, a reduction close to 24 MW is highlighted.

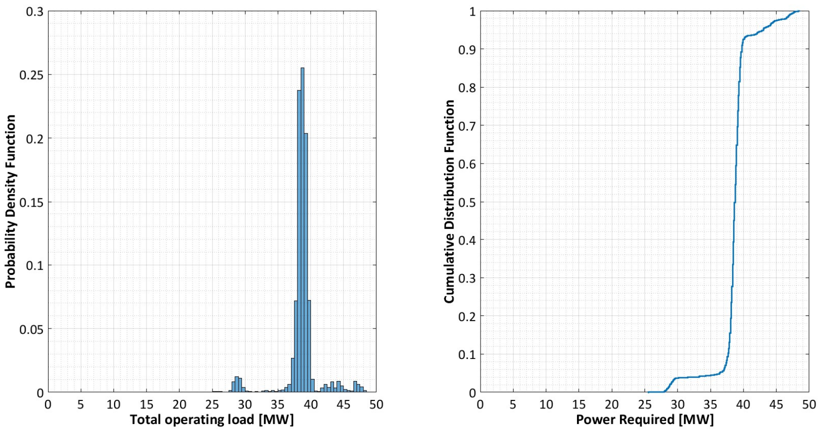


Figure 47 - Total operating load PDF and CDF in cruising at maximum speed condition for the cruise vessel

Considering the proposed operative scenarios, these reductions in the total operating load are mainly due to characterization of the load, especially for what concern the propulsive load. In fact, in the deterministic approach, being possible to select just a single deterministic value for the load factor corresponding to the propulsive engines, a precautionary approach was preferred.

On the other hand, the probabilistic approach allows the designer to characterize the operating load of these engines, considering all their possible working points. Furthermore, this characterization associates a probability of occurrence to each value of load power. For this reason, a significate difference in total operating load has been pointed out between the deterministic and probabilistic approaches, considering the cruise vessel.

Once the probability density functions and the probability of occurrence of each scenario have been evaluated and set, respectively, it would be possible to calculate the total operating load unconditioned. In this perspective, applying the theorem of total probability (e.g. explained and proposed in paragraph *3.9*) to the results proposed for each operative scenario, the unconditioned total operating load has been obtained and proposed in Figure 48.

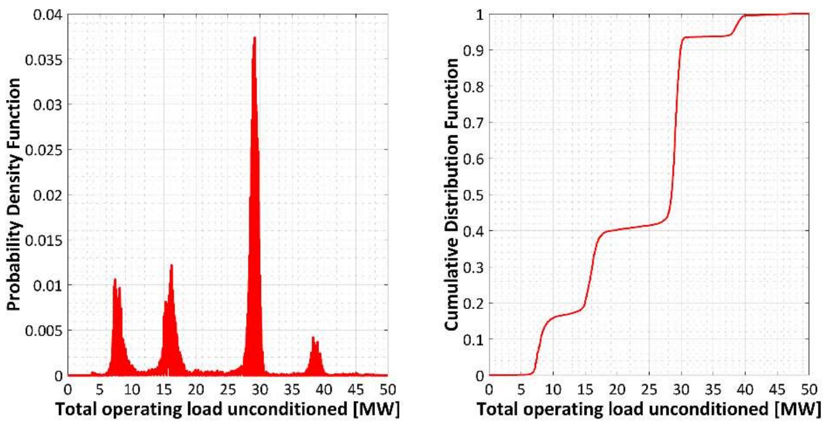


Figure 48 - Total operating load unconditioned PDF and CDF for the cruise vessel

The minimum, mean, maximum and percentile 95 values foe the total operating load unconditioned to the probability of each scenario are equal to 3.7 MW, 28 MW, 48.5 MW and 38.5 MW, respectively. The four steps (e.g. or modal values) shown in Figure 48 are due to four different propulsive conditions and configurations (i.e. manoeuvring, cruising at 10 kn, cruising at 20 kn and cruising at the maximum speed allowed).

Therefore, as happened for the bulk carrier, also for this case study, in order to prevent from the risk of under sizing the generation system, a risk assessment should be performed (as proposed in paragraph *3.10),* based on the unconditioned distribution. Results of the risk assessment are proposed in Table 20.

This analysis shows that a *1*-sigma approach would address to 122.6 hours per year, resulting in 20 minutes per day not covered by the generation. However, the on board automation system should managed this condition in order to prevent from blackout conditions. Another possible value, which is reasonable to consider in order to sizing the power generation system, is the percentile 99 of the total operating load unconditioned.

For this case study, this value is equal to 39 MW. Therefore, the total power installed for the power generation should be greater equal to 39 MW (e.g. without considering the scenarios of the greatest generator faults, as required by the normative [109]).

TABLE 20 - SIGMA APPROACH FOR RISK ASSESSMENT CONSIDERING THE TOTAL OPERATING LOAD UNCONDITIONED, FOR THE CRUISE VESSEL

Sigma	% Total Operating Load	Hours per year
1	98.6	122.6
2	100	0

3.12 Conclusions

As proposed in this chapter, recently, a sensible growth in the electric power installed on board ships has made the traditional approach to load prediction inaccurate, resulting in a significant oversizing of the power generation system. This, as already stated and explained, is mainly due to the deterministic factors applied in the traditional approach to EPLA. In fact, these factors have been evaluated based on dated shipboard power system and adopting very stringent hypothesis (e.g. central limit theorem). Therefore, in order to overcome the limits highlighted for the deterministic approach, a probabilistic approach to EPLA has been formulated, proposed and validated on two case studies.

The proposed probabilistic approach is primarily based on the statistical characterization of each electric device installed on board a ship. In this perspective, several random variables have been identified and probability density functions selected in order to describe the load behaviour of each device in each ship operative condition. Methods based on both assumptions and experimental data have been proposed in order to characterize each load. Then, methods for the statistical simulation have been described in order to combine each random variable accordingly to the system model developed. This, results in the total operating load evaluation in each ship operative scenario. Finally, a method to evaluate the total operating load unconditioned to the scenarios has been formulated.

This probabilistic approach, applied to the case studies ships (e.g. a bulk carrier and a cruise vessel) has led to significant reductions in the total operating load, which may result in a significant reduction in the size of the generation.

In this perspective, the formulation of an optimum problem to find the best technology, number of units and size of the power the power generation system could guarantee significant reductions in the costs of installation and management of the entire system. These aspects will be proposed and explained in details in Chapter 4, where the results obtained applying both the deterministic and probabilistic approaches to EPLA to the case studies have been adopted for the optimum generation sizing.

4 OPTIMAL SIZING OF SHIPBOARD DIESEL GENERATORS

Nowadays, the amount of electrical power generated on-board ships is drastically increased, especially for the well-known All Electric Ships (AES), where all the energy needed is supplied by the electrical power system. In this context, the traditional methods to calculate the total electric load of a ship and select the size of its generation system have become inadequate, since they are based on very dated assumptions and information. Therefore, this chapter introduces methodologies and algorithms that combine results obtained applying both a deterministic and the probabilistic electrical power load analysis approaches and an optimum problem formulation, adopted in order to optimally select the main characteristics for the diesel generators. Concerning the deterministic approach to electrical power load analysis (EPLA), the power demanded is calculated using the traditional approach based on load factors. On the other hand, the optimum problem is formulated considering as objective function the sum of management (i.e. the costs related to the fuel consumption) and installation costs of specific sets of generators (i.e. capex and opex). As a result, designers will be able to select the most efficient and reliable solution at design phase. These approaches are applied to two case studies in order to validate the formulation. The first case study is a bulk carrier ship, one of the most traditional ships. The second one is a large cruise vessel, already introduced in chapter 3, which presents an integrated electric ship (IES) configuration.

Results show that potential savings close to 40% and 50% are possible for the bulk and the cruise, respectively.

4.1 Context

In recent years, an increasing interest on energy efficiency and environmental issues has been revealed. These are two very closely related topics. In this perspective, concerning the maritime field, the International Maritime Organization (IMO) has recently realised measures to decrease Greenhouse Gases (GHG) emissions from ships, i.e. the Energy Efficiency Design Index (EEDI) and the Ship Energy Efficiency Management Plan (SEEMP).The EEDI is the most important technical measure and it aims at promoting the use of more energy efficient equipment and engines, which can also reduce GHG emissions for new ships [110]. From 1 January 2013, following an initial two year phase zero, when new ship design will need to meet the reference level for their ship type, the level is to be tightened incrementally every five years, as proposed in Figure 49. Therefore, the EEDI is expected to stimulate continued innovation and technical development of all the components influencing the fuel efficiency of a ship from its design phase. In conclusion, the EEDI is a non-prescriptive, performance-based mechanism that leaves to the industry the choice of which technologies to use in a specific ship design. On the other hand, the SEEMP is an operational measure that establishes a mechanism to improve the energy efficiency of a ship in a cost-effective manner.

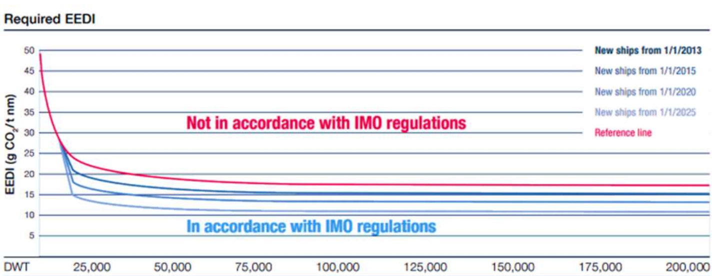


Figure 49 - EEDI CO_2 limits and phases

The SEEMP also provides an approach for shipping companies to manage ship and fleet efficiency performance over time using, for example, the Energy Efficiency Operational Indicator (EEOI) as a monitoring tool [111]. The SEEMP urges the ship owners and operators at each stage of the plan to consider new technologies and practices when seeking to optimise the performance of a ship, as proposed in Figure 50.

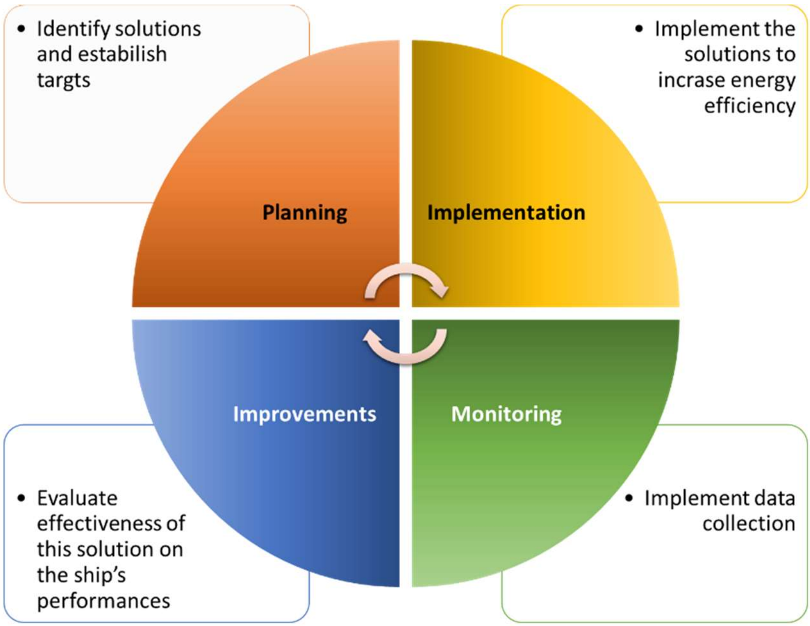


Figure 50 – SEEMP phases and impleentation

Several areas of action have been identified in order to improve the energy efficiency of ships. These include the optimization of the hull and the propeller shapes, new structural layouts with the use of high strength materials, shipbuilding technologies and the on-board systems design and technologies implementation, as proposed in Figure 51.

Figure 51 - Areas of action to improve ship's energy efficiency

In this context of technological innovation around the maritime world, one of the most active and promising sector is the one related to the on-board power system.

In the last decade, significant transformations and disruptive technological developments have been revealed in terrestrial power systems. This is direct consequence of an ever-deeper penetration of renewable energy sources (RES) into power generation. Introduction of RES into the grid has resulted in new challenges related to their stochastic behaviour and difficulties to forecast. Therefore, also traditional tasks such as the unit commitment and dispatch of resources needed to be revised to face these problems. In this context, several improvements (e.g. telecommunications, power electronics and mathematical methods) have helped to address these difficulties and improve the service provided by the grid. However, this extensive knowledge in “land-based” power generation and distribution systems has found limited use in the marine application, until now. Several solutions derived from “on-shore" applications may be implemented on board as well. In this perspective, one should note that shipboard power systems might be viewed as a marine microgrid.

In fact, microgrids are electrically and geographically small terrestrial power systems capable of operating connected to, or islanded from, a national grid. This can be exactly the definition for a shipboard power system, where generation and loads are present in a small and defined space, and the power system works in islanded configuration for the most of the time, although it can also operate connected to the land grid when the ship is at port.

In this context of continuous innovation, the last frontier for shipboard power systems is represented by AES [113] - [115], where each on-board system will be supported by electrical power. Whereby, the ever-increasing demand for safety, reliability, operational economy and environmental efficiency are the driving forces for increasing the use of the electrical power on board of different types of vessels.

While the methods of unit commitment [116], economic dispatch and contingency analysis[8], have been extensively used for decades in terrestrial power systems, their applicability to traditional shipboard systems has been limited. Nevertheless, at least in principle, these methods may provide potentially a significant operational cost reduction, along with improvements in planning and intelligent handling of the power plant [9].

Therefore, even one of the most traditional ship, the bulk carrier one, can be designed as a more innovative and eco-friendly ship, when detailed consideration is given to all the factors that may contribute to energy savings [34]. This perspective should be the driven objective of the whole ship life cycle, from design, through construction and operation, to recycling.

However, from the economic perspective, new technologies require large investments that can not be made if there is not a high degree of certainty concerning their long-term performance and economic balance between initial investments, running costs and revenues.

4.2 Literature review

In literature, methods and approaches have been proposed in order to correctly size and schedule generators, both in design and management phase. In [117], a method focused on power generation efficiency and energy cost decrease is proposed. In addition, a new load analysis method for marine vessels is proposed in this paper. The relationship of operation efficiency and load factor of generators is mathematically modeled and considered in the analysis. The problem is formulated as a non-differential combinational optimization problem, where the total generation cost during a whole voyage is minimized subject to system operation and technical constraints; in order to derive the optimal generators rated power and unit commitment using genetic algorithms as solver.

In [118], Doerry proposes new sizing methods for all-electric warships that are tied to operational effectiveness based on mobility mission tactical situations such as high speed transit, economical speed transit, and on station time. Moreover, the methods are sensitive to drag reduction efforts, temperature, and the ability to maintain speed in higher sea states. The aim is to optimize shipboard power and propulsion system life cycle cost while meeting operational requirements.

In [119], a method is proposed for determining the optimal size of the photovoltaic (PV) generation system, the diesel generator and the energy storage system in a stand-alone ship power system that minimizes the investment cost, fuel cost and the CO2 emissions. The power generation from PV modules on a ship relies on the date, local time, time zone, longitude and latitude along a navigation route and is different from the conditions of power systems on land. Thus, a method, which takes the seasonal and geographical variation of solar irradiations and temperatures along the route from Dalian in China to Aden in Yemen into account, for correcting the output of PV modules is developed in this paper. The proposed method considers five conditions along the navigation route to model the total ship load.

In [120], an optimum problem is developed and proposed in order to correctly and efficiently size the generation system. The power demanded is calculated using the traditional approach based on deterministic factors. The optimum problem is solved by using the Genetic Algorithms, and provide the optimal size, load factors and unit commitment for each generator in each ship operative scenario. However, they did not consider the possibility to adopt a probability density function (PDF) as input to the optimization problem, neither the installation costs for diesel generators into the objective function.

On the other hand, this chapter introduces methodologies and algorithms that combine results obtained applying the EPLA, i.e. both deterministic and probabilistic, and optimum problem formulations, used in order to optimally select the main characteristics for the diesel generators. These problems are formulated considering as objective function both management (i.e. the costs related to the fuel consumption) and installation costs of specific sets of generators. As a result, the designer will also be able to select the most efficient and reliable solution already at design phase.

4.3 Problem statement and formulation

The proposed formulation is focused on the optimal sizing and management of diesel generators, considering both the operational and investment costs. Despite the fact that some works in literature, i.e. [117] - [120], are focused on the optimal generator sizing, the formulation proposed in this thesis considers also the possibility to select generators with heterogeneous or homogeneous sizes and their installation cost. Moreover, a formulation to calculate the installation costs is also proposed.

It is to be noted that this kind of approaches present remarkable differences to the traditional methods used in marine power system design and management, despite in land application they could seem to be consolidated techniques. This is mainly due to the limited availability of data and measurements on board and to the nature of the ship design (i.e. almost every ship can be considered as a prototype).

4.3.1 Statement of the problem

The optimum problem formulated and developed in this chapter is actually focused on finding the best size for the diesel generators, considering inputs from the EPLA (e.g. both from deterministic and probabilistic approaches). The reference based on which it is defined the goodness of a certain solution are the installation and management costs for the power generation system.

In order to calculate the management costs of a certain solution (i.e. every generators configuration under exam) the fuel oil consumption (*FOC*) in a given condition has to be defined. For a specific operating condition, *FOC* is strongly dependent on the load factor (*GLF*) of the generators. Furthermore, it is also related to the efficiency of the generators (η), the power absorbed by the users (P_{load}), the line losses (P_{loss}), the number and the operation time (t) of each generators, the rated power (P_G), moreover on the specific fuel oil consumption (*SFOC*) that is characteristic of each generator, as defined in equation *(68)*.

$$FOC = f(GLF, \eta, P_{load}, P_{loss}, t, P_G, SFOC) \qquad (68)$$

It is worthy that, improving generators efficiency and load factors, a reduction in fuel oil consumption is possible. Considering the cost for the installation of defined diesel generators, this is strictly related to their main characteristics and on the technology selected (e.g. fixed speed, variable speed, diesel generator or dual fuel diesel generator).

The formulation of the optimum problem is here described in details and, in order to allow a better compression a brief introduction on Genetic Algorithms is proposed. It should be noted that, to better describe the whole problem and due to the limited number of variables, a mixed integer non-linear programming (MINLP) has been selected to formulate this optimum problem.

4.3.2 Problem input

Diesel generators (DGs) are under investigation to optimally size the shipboard generation system in this formulation, although other technologies can be applied in this perspective by only changing problem inputs (e.g. GA turbine, micro-turbine and fuel cells). Considering DGs, input to the problem are the technology selected between fixed and variable speed and the fuel selected between diesel oil and dual fuel solutions (e.g. which adopt both marine diesel oil MDO and liquefied natural GA LNG). Moreover, other useful information on DGs are the list of possible sizes, the total number of DGs to install (*G*), their rated power (P_G), power limits coming from manufacturer to prevent damage or premature aging (P_G^{MAX} and P_G^{MIN}), the DGs electrical efficiency (η), their specific fuel oil consumption ($SFOC_j$) and the specific unit cost depending on the size and technology selected (C_i). In Figure 52 and Figure 54, the specific fuel oil consumption curve in function of the loading condition of the DG is proposed for both the fixed speed and variable speed diesel generators, respectively. In Figure 53, a focus between the 10% and the 100% for the GLF is reported in order to allow a better comprension of the *SFOC* behaviour.

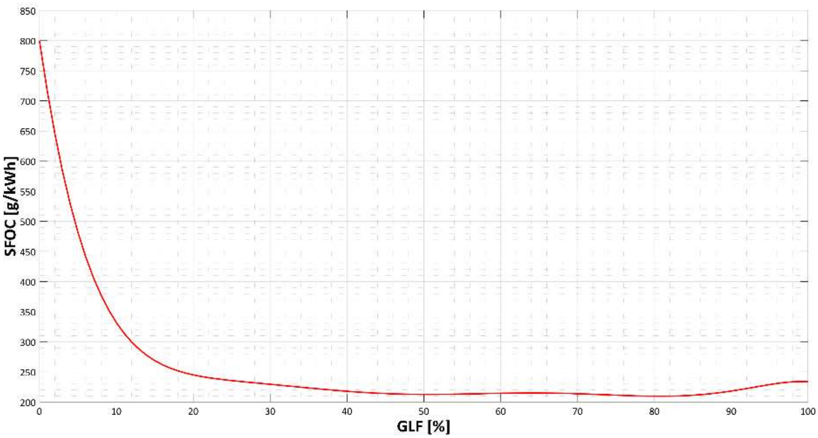


Figure 52 - Specific fuel oil consumption curve for fixed speed diesel generators

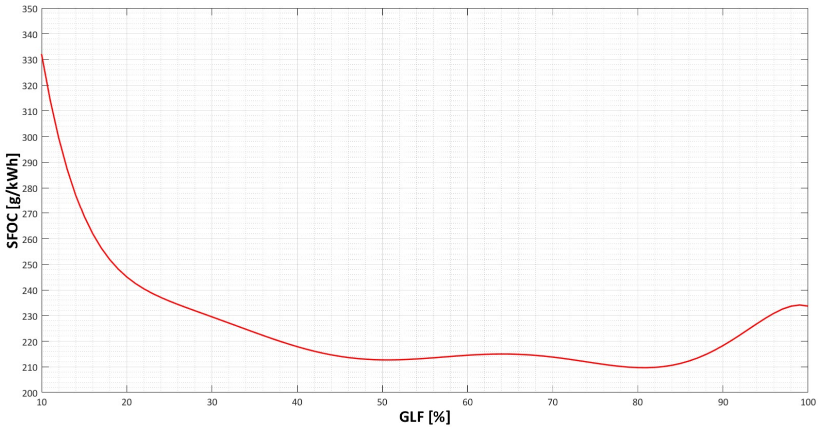


Figure 53 – Focus on the specific fuel oil consumption curve for fixed speed diesel generators

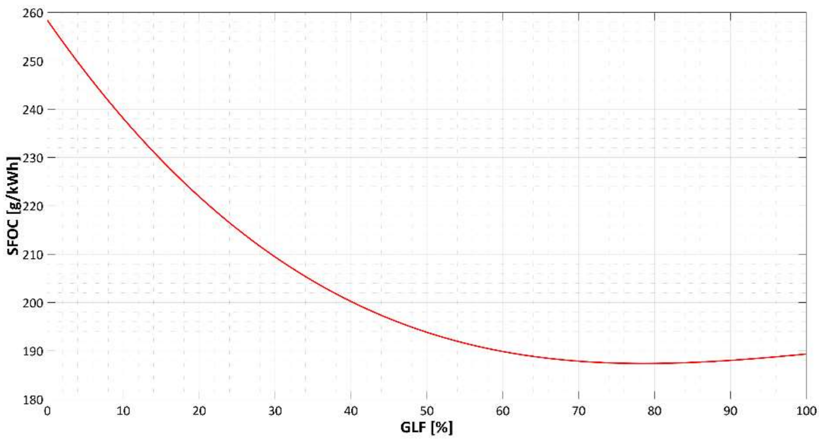


Figure 54 - Specific fuel oil consumption curve for variable speed diesel generators

As a result, it is possible to state that at low load condition, the *SFOC* is significant higher for the fixed speed solution, compared to the variable speed one. However, the installation cost for these solutions are different, and depending on the kind of ship, the fixed one can be better than the variable one or vice versa.

The efficiency of the diesel generators has been intrinsically considered into the *SFOC* curve reported in Figure 52 and Figure 54.

Other important input are those coming from the EPLA. In this case, a distinction is necessary between the deterministic method and the probabilistic one.

For the deterministic approach to EPLA, these inputs are the total power required to generation (P_{load}), the power wasted for losses (P_{loss}), the time spent (t_j) in each scenario j^{th} and the number of operative conditions considered (S). On the other hand, for the probabilistic approach to EPLA, the main inputs to the optimization problem are PDFs and CDFs for the power required to generation in each ship operative scenario j^{th}, the grid losses (P_{loss}) ,the probability of the ship to be in each operative condition considered ($P_{scenario_j}$), the time associated to each condition (t_j) and their total number (S).

All these input to the problem are summarized in Table 21. It is to be highlight that, in this chapter, simulations will be performed and presented considering, for simplicity, fixed speed diesel generators. However, this formulation can be easily applied considering both variable speed generators or dual fuel diesel generators.

TABLE 21 - INPUTS TO THE OPTIMIZATION PROBLEM

Parameter	Symbol
DG information:	
Technology	*FxS* (Fixed speed) *VrS* (Variable speed)
Fuel adopted	*MDO* (Marine diesel oil) *DLF* (Dual fuel)

Number of DGs	G
Rated power [kW]	P_G
Maximum power delivered [kW]	P_G^{MAX}
Minimum power delivered [kW]	P_G^{MIN}
Electric efficiency	η
Specific fuel oil consumption [g/kWh]	$SFOC_j$
Unit cost [\$/kW]	C_i
Deterministic EPLA information:	
Power required to generation (total load) [kW]	P_{load}
Power due to losses [kW]	P_{loss}
Time spent in each scenario [h]	t_j
Number of operative scenarios	S
Probabilistic EPLA information:	
PDF/CDF for the power required to generation (total load) [kW]	PDF_{load} - CDF_{load}
Power due to losses [kW]	P_{loss}
Probability of each scenario	$P_{scenario_j}$
Time spent in each scenario [h]	t_j
Number of operative scenarios	S

4.3.3 Problem variables

As already introduced, the problem is here formulated as a MINLP and Genetic Algorithms (GA) have been chosen in order to solve this problem due to their ability to account for integer variables, quadratic objective functions and constraints [121]. In this context, in order to account for integer variables it is required by the algorithm to define which variables are integer, otherwise, the variables are considered as continuous ones, although in this only the generator's load factors are considered as continuous variables

(GLF_{ij}). In this work, the generators state index u_{ij} and the different generator sizes are considered as integer variables. Actually, the first ones are defined as binary variables. In fact, each generators can be in function (i.e. u_{ij} = 1) or not in function (i.e. u_{ij} = 0) in each scenario. The second ones are defined through a vector of different options as reported in [117] and [120].

4.3.4 Objective function

Due to the aim of this problem, which is to select optimally the size and scheduling for DGs in design phase minimizing both the management and installation costs, the objective function proposed in equation *(69)* is the sum between these costs. The installation cost (IC) depends on the size of the DGs and on the technology selected (e.g. more information about that are available in paragraph 4.4, where the method is applied to the case studies). Concerning the management costs (MC), these are strictly dependent on the fuel oil consumption, which depends on the loading conditions and the technology selected. Furthermore, MC depend on the fuel selected. In fact, LNG is a cheaper fuel compared to the MDO and presents a lower environmental footprint, as well.

The objective function is here formulated and proposed in equation *(69)*.

$$\min_{P_G,u} \sum_{i=1}^{G} \left\{ \sum_{j=1}^{S} P_{ij} \cdot SFOC_{ij} \cdot T_j \cdot \frac{1}{\eta_{ij}} \cdot FC + (P_{G_i} \cdot C_{INST_i}) \right\} \tag{69}$$

Where, P_{ij}, $SFOC_{ij}$ and η_{ij} are the power delivered, the specific fuel oil consumption and efficiency for the i^{th} diesel generator at the j^{th} scenario, respectively. Moreover, t_j is the time spent t the j^{th} scenario, FC is the fuel oil unit cost, P_{G_i} is the rated power of the i^{th} diesel generator and C_{INST_i} its unit cost of installation. Finally, u is the variable identifying the DGs state.

4.3.5 Constraints of the problem

Constraints are formulated as equality and inequality function, with both linear and quadratic formulations. These, are constraints related to the correct management of the diesel generators, to balance the power demanded and the power delivered in each scenario and to allocate a certain reserve of power to prevent from blackout conditions. Moreover, others are related to the correct design of the power generation system. In the following, these constraints are presented in details.

- Power equilibrium constraint:

The power demanded by loads need to be matched by the power generated in order to control the ratio between grid voltage (V) and frequency (f) close to the operative set point. In the case that no energy storage system is installed on board the ship, diesel generators must deliver enough power to balance the load, in each ship operative condition and in each time step (t). This constraint is proposed in equation *(70)* and formulated as a linear equation, where P_{ij} is the power deliverd by the i^{th} diesel generator at the j^{th} scenario and P_{load_j} is the power required by the loads in the j^{th} scenario.

$$\sum_{i=1}^{G} P_{ij} = P_{load_j} \tag{70}$$

- Diesel generator power limits constraints:

These limits are necessary in order to prevent from damage and early deterioration of diesel generators. These limits are provided and suggested by manufacturers. These constraint are formulated as linear inequality equations and are proposed in equation *(71)*. Where, as already introduced, P_{ij}^{MIN} and P_{ij}^{MAX} are the minimum and maximum power available from diesel generators, as suggested by manufacturers.

$$P_{ij}^{MIN} \leq P_{ij} \leq P_{ij}^{MAX} \tag{71}$$

- Spinning reserve limit:

This unused capacity can be activated on decision of the Power Management System (PMS) and is provided by devices that are synchronized to the network and able to affect the active power. This limit is useful to prevent from blackout conditions and it is formulated as an inequality quadratic constraint, as proposed in equation *(72)*.

$$\frac{\sum_{i=1}^{G} P_{G_i} \cdot u_{ij} - P_{load_i}}{P_{load_i}} \leq SR \tag{72}$$

Where *SR* is the percentage of power allocated for the reserve, in reference to the total power required by loads.

- <u>Generator's state constraint:</u>

In the perspective of correctly selecting the best number of diesel generators and, moreover, to be sure that each diesel generator will be scheduled on at least in one scenario, a constraint must be formulated, as the one proposed in equation *(73)*.

$$\sum_{j=1}^{S} u_{ij} \geq 1 \tag{73}$$

- <u>Prevention from the loss of a generator constraint:</u>

In the case of loss of a diesel generator, the total load power must be balanced from generation in any case. This is also required by the international convention on Safety of Life at Sea (SOLAS) for what regard the power generation system design practice and requirements [109]. In this perspective, in equation *(74)* is proposed a constraint on the maximum number of diesel generators online in each ship operative condition. In fact, the reserve of power is guaranteed by the spinning reserve constraint in *(72)* and combined with equation *(74)* states that this reserve must be satisfied with *G-1* generators, being *G* the total number of installed generators. This is formulated as an inequality linear constraint in *(74)*.

$$\sum_{i=1}^{G} u_{ij} \leq G-1 \tag{74}$$

- Homogeneous size of generators constraint:

In order to account of the possibility to select generators with the same power rated, a constraint is here defined and implemented in equation *(75)* by imposing the equality between the rated power of the generators i^{th} and $i+1^{th}$. This constraint can be activated or not in the optimization problem, depending on the study of interest. This constraint is formulated as a linear equality one.

$$P_{i+1}=P_i \text{ for } i=1,\ldots,G \tag{75}$$

4.3.6 Auxiliary equations

Several equations have already been proposed to describe and model this problem. However, some parameters and characteristics have to be introduced through the use of auxiliary equations.

The first equation defines the unit cost (C_{I_i}) function for the diesel generators, depending on their rated power. In fact, this is formulated as a linear function of the diesel generator rated power P_{G_i} as proposed in equation (*76)*.

$$C_{I_i}= C_M + \frac{C_m\text{-}C_M}{P_{GEN_{Max}}\text{-}P_{GEN_{Min}}} \cdot (P_{G_i}\text{-}P_{GEN_{Min}}) \tag{76}$$

Where, C_M and C_m are unit costs for the maximum ($P_{GEN_{Max}}$) and minimum ($P_{GEN_{Min}}$) size available for diesel generators, respectively. The behaviour of C_{I_i} is proposed in Figure 55 (e.g. considering the DGs usually installed on board a cruise vessel) for a better understanding of the above.

It should be noted that, this installation cost represents also the cost related to the auxiliaries to be installed for machinery. It can also be interpreted as a penalty on the choice of small generators (e.g. these can divide the total generation power into many units).

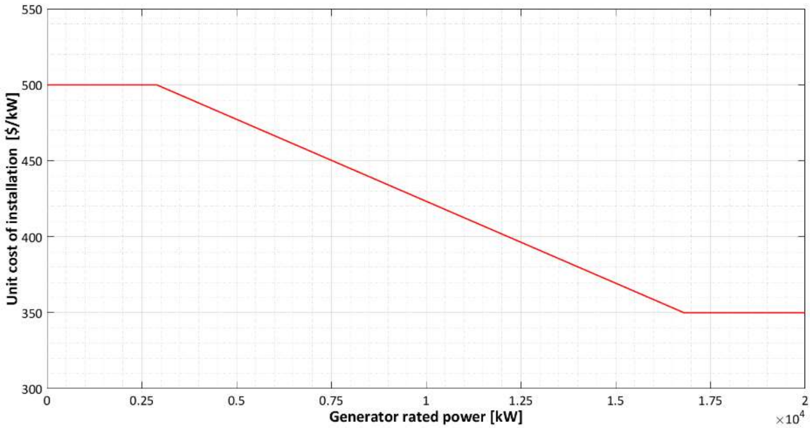


Figure 55 - Diesel generation unit cost of installation

A second auxiliary equation, proposed in *(77)*, defines the generator's power delivered P_{ij} as a function of the generator's loading condition GLF_{ij}, the rated power P_{G_i} and the state u_{ij} of the i^{th} generator.

$$P_{ij}=P_{G_{NOM}\,i}\cdot u_{ij}\cdot GLF_{ij} \tag{77}$$

Therefore, now it is possible to introduce the formulation adopted to calculate the specific fuel oil consumption of each diesel generator. In fact, this is a function of the rated and delivered power. In this formulation, a fifth order polynomial function has been selected to describe the $SFOC_{ij}$, and its behavior is proposed in Figure 52 and Figure 54, for fixed speed and variable speed DGs, respectively. In equation *(78),* the polynomial formulation is proposed, where, n is the order of the polynomial function (e.g. here set equal to 5), a_h is a known coefficient for h from zero to n, and GLF_{ij} is the loading condition for generator i^{th} at the j^{th} scenario.

$$SFOC_{ij}=\sum_{h=0}^{n} a_h\cdot GLF_{ij}^{\ h} \tag{78}$$

Closely related to this formulation is the definition of the electrical efficiency of the generators, as proposed in the equation *(79)*(82).

$$\eta_{ij}=\eta_{j_{MAX}}+\left(c_1 \cdot e^{-\left(c_2 \cdot GLF_{ij}\right)}\right) \tag{79}$$

Where, η_{ij} is the efficiency of generator i^{th} at the j^{th} scenario, $\eta_{j_{MAX}}$ is the maximum efficiency allowed, c_1 and c_2 are coefficients used to model the exponential curve of η_{ij} and GLF_{ij} is the loading condition.

4.3.7 Genetic algorithms description

Charles Darwin stated the theory of natural evolution in the *"origin of species"*. Over several generations, biological organisms evolve based on the principle of natural selection *"survival of the fittest"* to reach certain remarkable tasks. In nature, an individual in population competes with each other for resources like food, shelter and so on. Due to this selection, poorly performing individuals have less chance to survive, and the most adapted (i.e. *"fitted"*) individuals produce a relatively large number of offspring's.

It can also be noted that during reproduction, a recombination of the good characteristics of each ancestor can produce *"best fit"* offspring whose fitness is greater than that of a parent. After a few generations, species evolve spontaneously to become more and more adapted to their environment [122].

In this perspective, Genetic Algorithms (GA) are a direct, parallel, stochastic method for global search and optimization, which imitates the evolution of the living beings, described by Charles Darwin. GA are part of the group of evolutionary algorithms (EA). The evolutionary algorithms use the three main principles of the natural evolution: reproduction, natural selection and diversity of the species, maintained by the differences of each generation with the previous. GA work with a set of individuals, representing possible solutions of the task. The selection principle is applied by using a criterion, giving an evaluation for the individual with respect to the desired solution. The best-suited individuals create the next generation.

For the genetic algorithms, the chromosomes represent set of genes, which code the independent variables. Every chromosome represents a solution of the given problem. Individual and vector of variables will be used as chromosomes. On the other hand, the genes could be Boolean, integers, floating point or string variables, as well as any combination of the above. A set of different chromosomes forms a generation.

As already stated, in nature, the selection of individuals is performed by survival of the fittest. The more one individual is adapted to the environment the bigger are its chances to survive and create an offspring and thus transfer its genes to the next population. Therefore, as a first step in order to start their process, GA need to produce an initial population of chromosomes, which contains the possible solutions. This population is than tested with the environment to find the most suited individuals by using a fitness function. Further, until the termination conditions are satisfied the following process will be repeated, as proposed in Figure 56.

The first step in the reproduction process is the recombination or crossover. Here, the genes of the parents are used to form an entirely new chromosome. The typical recombination for the GA is an operation requiring two parents, but schemes with more parents are also possible. The newly created by means of selection and crossover population can be further applied to mutation. Mutation means, that some elements of the DNA are changed. In the terms of GA, mutation means a random change of the value of a gene in the population. The chromosome, which gene will be changed and the gene itself are chosen by random, as well. Finally, the fitness of the modified individuals is calculated and a new population is generated.

When the termination condition are satisfied, the best solution is presented as the solution to the problem under exam. In the following, the main steps of the algorithm are explained to allow a better compression of GA.

One of the most important step in the algorithm is the selection of the individuals for reproduction. The Selection is a process, in which the individuals which will be applied to the genetic operations and which will create the offspring population are chosen. The selection has two main purposes: chose the most perspective individuals, which will take part in the generation of next population or will be directly copied. Secondly, it gives an opportunity to individuals with comparatively bad value of the fitness function to take part in the creation process of the next generation. This allows us to preserve the global character of the search process and not allow a single individual to dominate the population and thus bring it to local extremum. The probability of each individual to be selected is calculated as the proportion of its fitness function to the sum of the fitness functions of all individuals in the current generation.

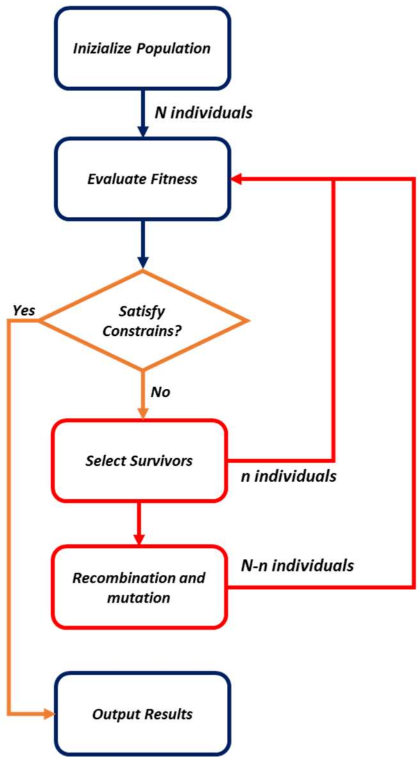
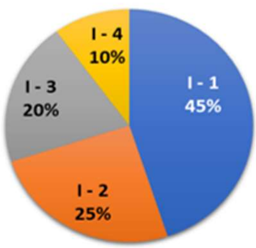


Figure 56 - Genetic algorithms steps

It should be noted, that this type of selection is for maximization problems, whereas it searches always for the minimum. This is done by recalculating the fitness values in such a way, that the best individuals (i.e. minimal function value) receive the maximal fitness and vice versa. In crossover step, individuals chosen by selection are recombined with each other and new individuals will be created. The aim is to get offspring individuals, that inherit the best possible combination of the characteristics (i.e. genes) of their parents. For the crossover or recombination of parents, several methods can be applied. Traditionally, the roulette wheel method is the most used. This considers a circle divided into N sectors, where N is the number of individuals in the population. The arc of each sector is proportional to the selection probability of the corresponding individual. After each rotation of the wheel, the individual opposite the “selection arrow” is chosen. You can think about the real roulette wheel, where at each turn, the ball stops randomly at number. The individuals are sorted according to the value of their fitness function and then they are assigned a rank. The rank of the best individual is 1, of the second best 2 and so on as proposed in Figure 57. The newly created by means of selection and crossover population can be further applied to mutation. Mutation means, that some elements of the DNA are changed. Those changes are mainly due to mistakes during the copy process of the parent’s genes. In the terms of GA, mutation means random change of the value of a gene in the population.



Individuals	Fitness function	Probability
I - 1	4	0.45
I - 2	3	0.25
I - 3	2	0.2
I - 4	1	.01

Figure 57 - Genetic algorithms crossover roulette wheel approach

Finally, the elite of individuals chosen from the selection are combined with those who passed the crossover and mutation, and form the next generation. Therefore, the algorithm can pass to another iteration until when constraints are satisfied.

4.3.8 Solver settings

As already, stated, Genetic algorithms are the solver applied to this methodology. GA are one of the most effective solver present in Matlab to find a global solution to highly nonlinear problems, as the one proposed in this study. Furthermore, GA can be applied to solve problems that have a stochastic objective function. Matlab's *"optimization toolbox"* allows to set some parameters of the solver such as:

- Specify the *population size*, which for default is equal to 50,
- Set the *crossover rate* value, specifies the fraction of each population, other than elite children, that are made up of crossover children. A crossover fraction of 1 means that all children other than elite individuals are crossover children, while a crossover fraction of 0 means that all children are mutation children. Crossover children are created by combining the vectors of a pair of parents,
- Set the *elite count* set the number of individuals with the best fitness values in the current generation that are guaranteed to survive to the next generation. These individuals are called elite children. The default value of Elite count is 2. Elite children are the individuals in the current generation with the best fitness values. These individuals automatically survive to the next generation.

All these options and their effect on the next generation of individuals are graphically shown and explained in Figure 58.

The values that have been selected (e.g. after a sensibility analysis) for these options in this formulation are 800 of individuals for the population size (PN), crossover rate (CR) equal to 0.55 and, finally, an elite count equal to 0.0065 multiplied for PN.

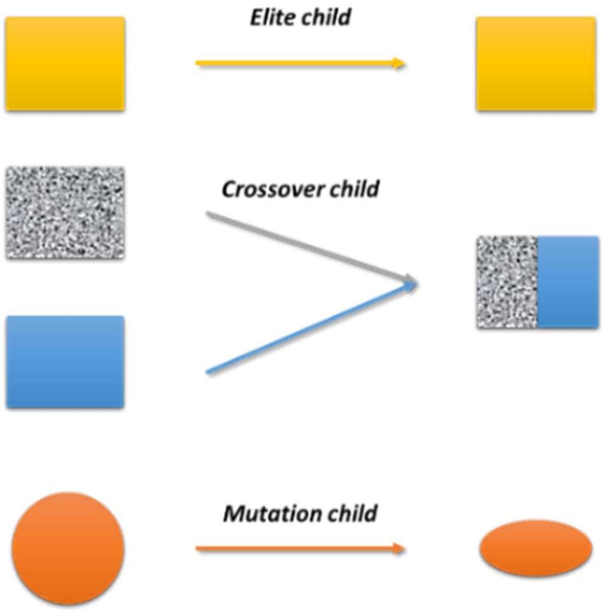


Figure 58 - Genetic algorithms options and their effect on the next generation

4.4 Case studies

In order to test and validate this methodology, two case studies have been selected, which can represent two very different shipboard power systems and ship typology. The first case study is a bulk carrier ship, which probably is the most traditional merchant ship. In fact, it presents a shipboard power system that powers only few users on-board, such as auxiliaries, lighting system and HVAC. On the other hand, the second one is a large cruise ship that present an integrated electrical system (e.g. where all the main users are powered by the shipboard power system).

It is to be highlighted that, in this case, also propulsion system is powered by electricity. These ships, together with their main inputs to the problem, are here described and proposed. In addition, the main inputs obtained from the EPLA (i.e. both deterministic and probabilistic ones) will be presented and their results compared applying this method to optimally select the power generation system size and configuration.

4.4.1 Bulk carrier ship

This first case study ship has already been introduced in *3.11.1*, where the probabilistic approach to EPLA has been tested and validated. Moreover, considering the aim of this chapter, the main results yielded from the deterministic EPLA are here summarized in Table 22. These values are core input information of this methodology to size optimally diesel generators. It is possible to highlight that the power demand change significantly scenario by scenario and the most critical one is the *"loading/unloading"* one, where 1068 kW are required.

TABLE 22 - BULK CARRIER SHIP EPLA RESULTS, DETERMINISTIC APPROACH

Scenario	**In Port**	**Man.**	**Cruising**	**Loading-Unloading**
Mission Times Horizon [h]	96	12	384	228
Load Power [kW]	433	724	610	1068

Furthermore, in Table 23, the scheduling developed at design phase of the ship is proposed. Furthermore, applying the specific fuel oil consumption curve proposed in Figure 54 and the installation cost proposed in equation (*76)* and Figure 55, a total cost of a hypothetical mission of one month has been evaluated. It is to be noted that, the installation costs have been distributed over the whole ship' life horizon, which typically is equal to 25 years.

TABLE 23 - DIESEL GENERATORS SCHEDULING AT DESIGN PHASE

Scenario	u_1	u_2	u_3	GLF_1	GLF_2	GLF_3
In Port	OFF	ON	OFF	0.0	60.1	0.0
Manoeuvring	OFF	ON	ON	0.0	50.3	50.3
Cruising	ON	OFF	OFF	84.7	0.0	0.0
Loading – Unloading	ON	OFF	ON	74.2	0.0	74.2

As a result, it has been possible to calculate the monthly cost for both installation and management of the diesel generators by dividing the total costs for the total number of months in 25 years. This cost will be considered as base line for the test and validation of the proposed methodology and every results will be compared to it. For this case study, the monthly cost calculated from design phase information has been evaluated equal to 3387$, 87908$ and 91295$, for the installation (IC), management (MC) and total monthly costs (TC), respectively. Applying the probabilistic EPLA to the bulk carrier ship, interesting results have been reached and proposed (in Chapter 3). These are PDFs and CDFs for the total operating load in each ship operative condition considered (e.g. as proposed in Figure 59 for the cruising scenario).

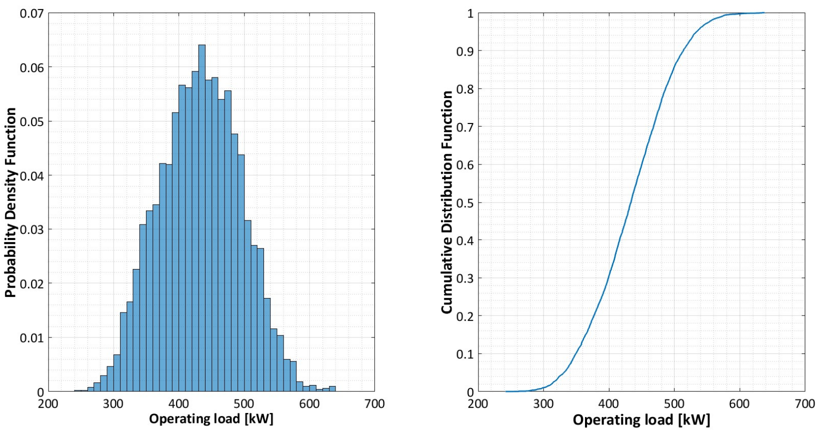


Figure 59 - PDF and CDF of the total operating load in cruising scenario

Moreover, after the un-conditioning process, also PDF and CDF for the total operating load unconditioned are available, as proposed in Figure 60.

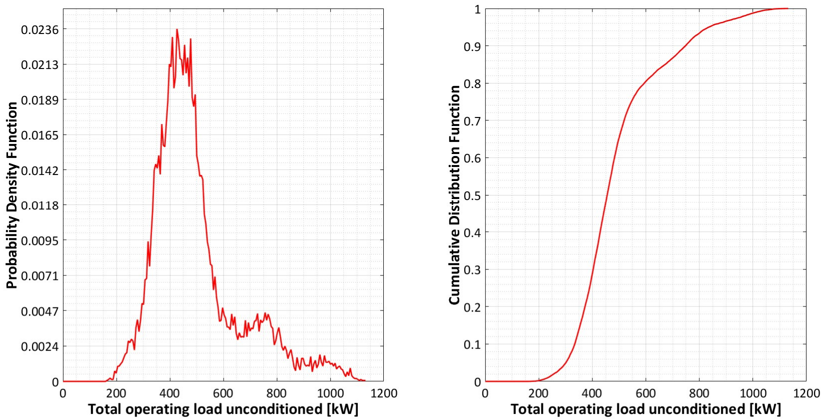


Figure 60 - PDF and CDF of the total load for the bulk carrier ship

Considering Figure 60, it is possible to highlight that there are three points with relevant density of probability (e.g. around 500, 750 and 950 kW). These are actually related with the total operating load modal values in each ship operative scenario (e.g. shore, manoeuvring, cruising and loading/unloading) considered.

In this context, useful information for the scheduling of diesel generators are the modal and mean values for the operating load in each ship operative condition considered. On the other hand, the maximum value (e.g. close to 1200 kW) or the percentile 99 value (e.g. close to 1 MW) are significant information to identify the total power (e.g. the sum of the rated power of each diesel generator) to install for the power generation system.

4.4.2 Large cruise vessel

The second case study proposed in this chapter to validate and test the proposed optimal algorithm is a large cruise vessel. This ship, as it happened for the bulk carrier one, has already been introduced and described in *3.11.2*, when the probabilistic approach to EPLA has been applied to the case studies in order to test its performances compared to the deterministic one. In this context, results obtained applying the deterministic EPLA, derived from those obtained at design phase, are proposed in Table 24.

TABLE 24 – LARGE CRUISE SHIP EPLA RESULTS, DETERMINISTIC APPROACH

Scenario	**Shore**	**Man.**	**Cruising 10kn**	**Cruising 20kn**	**Cruising Max**
Times Horizon [h]	155	5.2	52	168	339.8
Load Power [kW]	17920	33208	31228	43158	62898

The specific fuel oil consumption and installation cost formulations have been applied in order to calculate the monthly base cost, which will be compared to those obtained applying this methodology. Considering the design scheduling reported in Table 25 and the cost of the fuel set to 660 $/t, the Mission Costs (MC) results equal to 4665400$.

TABLE 25 - DIESEL GENERATORS SCHEDULING AT DESIGN PHASE FOR THE LARGE CRUISE SHIP

	Shore	**Man.**	**Cruising 10kn**	**Cruising 20kn**	**Cruising Max**
Time Horizons [h]	155	5.2	52	168	339.8
Scheduling	G1-G2	G1-G2-G3	G3-G4-G5	G3-G4-G5-G6	All gen. on
GLF [%]	71.1	87.9	82.6	85.6	83.2
SFOC [g/kWh]	278.5	255.5	256.5	258.7	255.5

This cost is to be considered in addition to the installation costs (IC) for the six diesel generators equal to 99617$. The resulting total monthly cost (TC) is 4765000$.

Applying, the probabilistic EPLA also to this case study, the results proposed in Figure 61 and Figure 62 have been pointed out (e.g. all results have already been proposed in chapter 3).

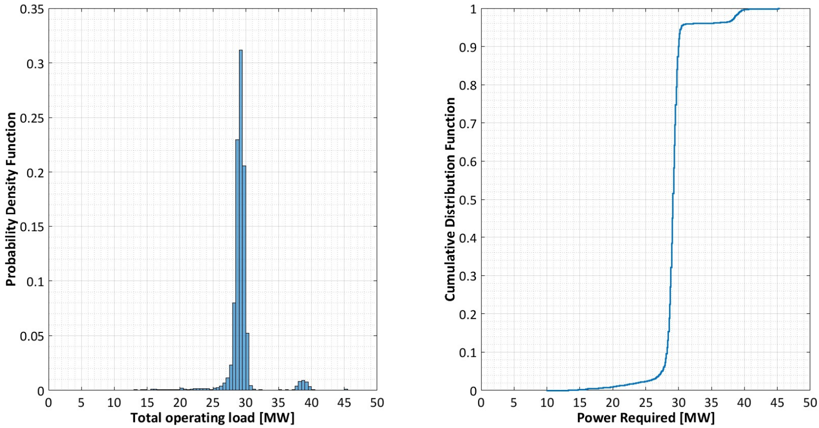


Figure 61 - PDF and CDF of the total operating load in cruising scenario

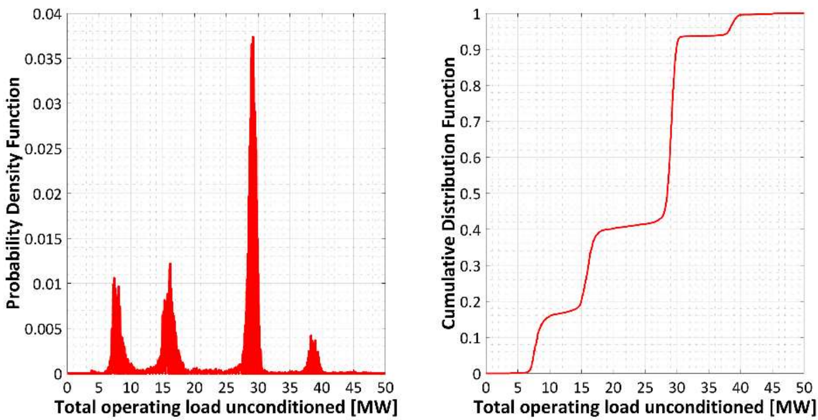


Figure 62 - PDF and CDF of the total load for the cruise ship

It is possible to highlight that there are five points with significant density of probability (i.e. around 4, 8, 16, 29, 39 MW). These are strictly related with the total operating load modal values in each ship operative scenario (e.g. shore, manoeuvring, cruising at 10kn, cruising at 15kn and cruising at 20kn) considered. In this context, the modal and mean values are useful inputs in order to select how many generators should be in service (i.e. scheduling problem) and how they are averagely loaded in each scenario. On the other hand, the maximum value (e.g. close to 48 MW) or the percentile 95 value (e.g. close to 38 MW) are significant information in order to calculate the total power to install for the power generation system.

4.5 Results

The method proposed in this chapter to optimally select the size and schedule the diesel generators has been applied to the case studies introduced above. This paragraph report and analysis the results yielded with this methodology, combined with both deterministic and probabilistic inputs, derived from the EPLA. In this perspective, also in design phase it should be possible to account for the management (e.g. scheduling and loading condition) of the power generation system, as well as to size them optimally. The optimal number of generators is not studied in this work due to the need of further considerations and information about weights and volumes for both the diesel generators and the engine rooms that are not available, unfortunately.

Simulations have been performed for different configurations, e.g. using the traditional electrical power load analysis results has inputs, considering both generators with homogeneous and non-homogeneous size. Furthermore, the same simulations have been performed considering the results from the probabilistic EPLA as inputs, considering the modal values of the operating load in each scenario instead of the maximum assumed by the traditional approach in order to identify the normal operating load in each operative scenario.

In order to perform the optimal sizing and unit commitment, the total electrical power installed on-board the ship should be enough to guarantee sufficient generation power, in case of occurrence of a load peak (e.g. considered equal to the percentile 99 of the operating load).

Due to reasons of synthesis, in this work it only the use of variable speed diesel generators has been studied. Therefore, calculations on the fuel oil consumption are performed assuming the specific fuel oil consumption curve for variable speed DGs. This curve has only one local minimum placed close to the 75-80% of the nominal power, unlike the one proposed for fixed speed diesel generators. However, considering the curve for the fixed speed DGs, two local minima are pointed out, which are positioned close to the 50% and 80% of the rated power. These two local minima may influence the results of the optimization in case the GA's parameters have not been calibrated adequately in order to serch for the absolute minimum rather than a local one.

In Table 26 a scheme of the four simulation performed for each case study is proposed. As already stated, the base line conditions allow comparisons with the results derived from the optimization, for this reason are here reported for each case study to allow a better comparison.

In order to verify the goodness of the optimization algorithm, this is applied to the case studies adopting as inputs information obtained from the deterministic approach to EPLA (i.e. the same conditions used by the designers to select the generators size and scheduling).

TABLE 26 - SIMULATION PLAN FOR BOTH THE CASE STUDIES

Simulation	**EPLA approach**	**Sizing approach**
A	Deterministic	Homogeneous
B	Deterministic	Heterogeneous
C	Stochastic	Homogeneous
D	Stochastic	Heterogeneous

This optimization is performed for both homogeneous and heterogeneous sizes of the diesel generators, for both the bulk carrier and the cruise ship.

4.5.1 Bulk carrier

The first case study, the bulk carrier ship, has already been presented. Considering this case study, the optimum problem formulated and proposed in this chapter is applied. Moreover, its result are proposed and analysed for each simulation reported in Table 26.First of all, the base line conditions for this case study are presented to allow a comparison with the results obtained from the proposed formulation.

- Base line condition:

The design conditions for the bulk carrier have already been presented in Table 23. The management (or mission) cost MC, evaluated with design information are equal to 77402$ per month. Moreover, considering three diesel generators sized 720 kW each, and applying equation (*76)*, it is possible to state that at design condition the installation costs result equal to 3387$ per month. Therefore, the total monthly cost of this bulk carrier ship, at design condition, is equal to 80429$, as proposed in Table 27.

TABLE 27 – BASE LINE COSTS FOR THE BULK CARRIER

Mission cost [k$]	**Installation cost [k$]**	**Total cost [k$]**
77.4	3.39	80.43

Considering these values as a base line, it is possible to present the results of the simulation and allow a comparison with what expected at design phase.

In simulations C and D, for both the case studies, inputs derived from the results of the probabilistic EPLA are used to size the power generation system. These are the modal values for the PDFs obtained in each scenario under exam (e.g. as the one proposed for the cruising scenario in Figure 59) and the 95 percentile value for the CDF of the total operating load unconditioned from the operative conditions (e.g. the one proposed in Figure 60). These modal values are summarized in Table 28 to allow comparison with the deterministic case. The 95 percentile of the total operating load (e.g. unconditioned from the scenarios) is equal to 1 MW.

Therefore, the total power installed for the power generation system must be greater than this value.

TABLE 28 – RESULTING MODAL VALUES YIELDED APPLYING THE PROBABILISTIC APPROACH TO EPLA FOR THE BULK CARRIER

Parameter	Shore	Manoeuvring	Cruising	Loading-Unloading
Modal value [kW]	353.2	455.5	410	579

- <u>Simulation A:</u>

As proposed in Table 26, this first simulation considers as inputs to the optimal problem the results from the deterministic EPLA performed from by the shipyard and reported in Table 22. Moreover, in order to size the diesel generators with the same rated power, the homogeneous constraint proposed in *(75)* has been activated in this simulation. The size selected for the three diesel generators installed on board the case study are reported in Table 29, where three diesel generators of 688 kW are proposed as best solution. The total amount of power installed for the generation system is equal to 2064 kW, instead of the 2160 kW installed at design phase (e.g. a saving in power installed close to 100 kW), with benefits for both the costs, volume and GHG emission.

TABLE 29 – DIESEL GENERATOR SIZES AND TOTAL POWER ISTALLED, SIMULATION A

G1 [kW]	G2 [kW]	G3 [kW]	Total power installed [kW]	Difference with the base line [kW]
688	688	688	2064	96

Moreover, in an EEDI perspective, the reduction of the power installed is advantageous in order to guarantee the respect of the limits imposed by the normative [110].

The scheduling and loading conditions pointed out by the optimal problem are proposed for the three diesel generators in Table 30. Due to the constraint proposed in *(74)*, at least one diesel generator is always shut down in each scenario and it can be started up in case of failure of another generator.

TABLE 30 – RESULTS YIELDED BY APPLYING THE DETERMINISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE BULK CARRIER

	Shore	**Manoeuvring**	**Cruising**	**Loading-Unloading**
DG Scheduling	G1	G1-G3	G2	G1-G3
GLF [%]	62.9	52.6	88.7	77.6
SFOC [g/kWh]	219.8	216.3	210.3	217.2

As a result of the scheduling and loading conditions for the diesel generators proposed in Table 30, applying the cost of 660$/t for the marine diesel oil (MDO) to the specific fuel oil consumption of each generator, the monthly mission cost (MC) are equal to 58585$.

Considering the installation of three diesel generators rated 688 kW each, the total installation costs in a monthly perspective are equal to 3253 $. Therefore, the total monthly costs is equal to 61842 $. This corresponds to a net monthly saving of 29450 $ (e.g. the 32.3%).

Considering one year of time horizon, this corresponds to a saving of more then 353400 $, as proposed in Table 31.

TABLE 31 – COSTS AND SAVINGS ANALYSIS FOR THE DETERMINISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE BULK CARRIER

MC [k$]	**IC [k$]**	**TC [k$]**	**Savings Monthly [k$]**	**Savings Yearly [k$]**	**Savings Percentage [%]**
58.59	3.25	61.84	29.45	353.4	32.3

- <u>Simulation B:</u>

Simulation B considers the load power evaluated by deterministic EPLA as inputs. Differently from simulation A, in this case, heterogeneous sizes for the diesel generators are allowed. This is possible by deactivate constraint *(75)*. The resulting sizes for the three diesel generators are summarized in Table 32. The total power installed for the power generation system, in this case, is equal to 1224 kW, 936 kW less than at design condition.

TABLE 32 – DIESEL GENERATOR SIZES AND TOTAL POWER ISTALLED, SIMULATION B

G1 [kW]	**G2 [kW]**	**G3 [kW]**	**Total power installed [kW]**	**Difference with the base line [kW]**
388	500	336	1224	936

However, considering the scheduling and loading conditions proposed in Table 33, it is possible to note that, as it happened in simulation A, also in this one all the constraints are respected, especially the one concerning the possible failure of one generator. In fact, the maximum number of diesel generators up in each scenario is two (e.g. one generator can be started up in case of failure of another one). The loading conditions of the diesel generators are very close to their optimum point (e.g. 85%), therefore, the specific fuel oil consumptions are lower than those expected in design phase.

TABLE 33 – RESULTS YIELDED BY APPLYING THE DETERMINISTIC APPROACH TO EPLA WITH HETEROGENEOUS SIZES FOR THE BULK CARRIER

	Shore	**Manoeuvring**	**Cruising**	**Loading-Unloading**
DG Scheduling	G2	G1-G2	G2-G3	G1
GLF [%]	86.6	89.9	86.6	88.7
SFOC [g/kWh]	210.7	210.4	210.7	210.3

This fuel saving are directly reflected on the savings related to the management of the ship, the monthly mission cost (MC). In fact, this cost is equal to 57684$. On the other hand, with the sizing proposed in Table 32, the monthly installation cost (IC) for the diesel generators is set equal to 2457$. Thus, the total monthly cost for the bulk carrier, considering the results yielded from simulation B are equal to 60140$, as reported in Table 34.

This total cost represents a decrease in the ship's monthly costs of approximately 31155$. Otherwise, considering a mission horizon of one year, the net savings are over 373850$. Finally, this configuration allows savings close to 34% of the base line total cost proposed in Table 23.

TABLE 34 – COSTS AND SAVINGS ANALYSIS FOR THE DETERMINISTIC APPROACH TO EPLA WITH HETEROGENEOUS SIZES FOR THE BULK CARRIER

MC [k$]	**IC [k$]**	**TC [k$]**	**Savings Monthly [k$]**	**Savings Yearly [k$]**	**Savings Percentage [%]**
57.68	2.46	60.14	31.15	373.8	34.1

Therefore, the results obtained in simulation B highlight an effective possibility to decrease both the fuel consumption (e.g. and the GHG emission as a consequence) and the costs related to the ship management by introducing diesel generators with different sizes. In fact, if the total operating load prediction is accurate, the sizing of the power generation system can be more efficient and reliable, also considering a fractioning of the power installed to improve the diesel generators performances.

- <u>Simulation C:</u>

In this simulation, the load power evaluated by probabilistic EPLA proposed in Table 28 are considered as inputs. Similar to simulation A, also in this case homogeneous sizes for the diesel generators are selected. This is possible by activating the constraint reported in equation *(75)*. The sizes resulting for the three diesel generators are summarized in Table 35. The total power installed for the power generation system, in this case, is equal to 1920 kW, 240 kW less than at design condition and 144 kW less than the deterministic case in simulation A.

TABLE 35 – DIESEL GENERATOR SIZES AND TOTAL POWER ISTALLED, SIMULATION C

G1 [kW]	**G2 [kW]**	**G3 [kW]**	**Total power installed [kW]**	**Difference with the base line [kW]**
640	640	640	1920	240

Also in this simulation, the optimum scheduling shows that the maximum number of diesel generators up in each scenario is two (e.g. one generator can be started up in case of failure of another one). In this simulation, the monthly mission cost resulting from the optimum scheduling reported in Table 36 are equal to 46870$. On the other hand, with the installation of three diesel generators sized 640 kW each, a monthly installation cost of 3050$ is pointed out. Therefore, the monthly total cost are equal to 49920$, in this conditions.

Finally, it is to be highlighted that savings close to 41375$, 496500$ and close to 45% are possible considering a monthly, yearly and parentage perspective, respectively. These results are here summarized in Table 37.

TABLE 36 – RESULTS YIELDED BY APPLYING THE PROBABILISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE BULK CARRIER

	Shore	**Manoeuvring**	**Cruising**	**Loading-Unloading**
DG Scheduling	G1	G3	G1	G2
GLF [%]	55.2	71.2	64.0	90.5
SFOC [g/kWh]	216.8	220.6	220.1	210.5

TABLE 37 – COSTS AND SAVINGS ANALYSIS FOR THE PROBABILISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE BULK CARRIER

MC [k$]	**IC [k$]**	**TC [k$]**	**Savings Monthly [k$]**	**Savings Yearly [k$]**	**Savings Percentage [%]**
46.87	3.05	49.92	41.37	496.5	45.3

- Simulation D:

Simulation D considers probabilistic inputs, as already proposed for simulation C. However, differently from the latter, simulation D allow the possibility to select diesel generators of different sizes by deactivating the homogeneous size constraint reported in equation *(75)*.

The optimal sizes selected by the proposed algorithm are reported in Table 38. In this context, three diesel generators are selected, two sized 336 kW and the last one sized 500 kW. This sizing result very similar to the one proposed in simulation B, although the power installed is lower than in simulation B. In fact, the total power installed is equal to 1172, which is the lowest value pointed out by these simulations, with a reduction close to 990 kW compared to the design condition.

TABLE 38 – DIESEL GENERATOR SIZES AND TOTAL POWER ISTALLED, SIMULATION D

G1 [kW]	G2 [kW]	G3 [kW]	Total power installed [kW]	Difference with the base line [kW]
336	336	500	1172	988

This significant reduction in power installed is advantageous for weight aspects and in the perspective of the EEDI. In fact, the index formulation penalizes those ships that install huge amount of power to perform a task. Therefore, with this sizing, this ship may perform the same mission with a reduction in the total power installed.

The optimum algorithm provides the diesel generators scheduling and their optimum loading conditions, which should minimize the mission cost related to the fuel oil consumption, as proposed in Table 39.

TABLE 39 – RESULTS YIELDED BY APPLYING THE PROBABILISTIC APPROACH TO EPLA WITH HETEROGENEOUS SIZES FOR THE BULK CARRIER

	Shore	Manoeuvring	Cruising	Loading-Unloading
DG Scheduling	G1 – G2	G1 – G3	G3	G1 - G2
GLF [%]	52.6	54.5	82.0	86.2
SFOC [g/kWh]	216.3	216.6	213.6	210.9

The monthly mission cost, derived from the optimum scheduling and loading conditions proposed in Table 39, is equal to 46190 $, which is the lowest obtained in this work for this case study. Installation cost resulting from the sizing are equal to 1930 $ per month.

TABLE 40 – COSTS AND SAVINGS ANALYSIS FOR THE PROBABILISTIC APPROACH TO EPLA WITH HETEROGENEOUS SIZES FOR THE BULK CARRIER

MC [k$]	IC [k$]	TC [k$]	Savings Monthly [k$]	Savings Yearly [k$]	Savings Percentage [%]
46.19	1.93	48.13	43.16	517.95	47.3

Finally, the total cost, which is the sum of mission cost and installation cost, is here equal to 48130$ per month, a monthly reduction of 43165$ compared to the base line condition propose in Table 27. In one year of mission perspective, this reduction is equal to 517950$that is close to the 47.3% of the total cost in design conditions, as summarized in Table 22.

The results yielded for the second case study, the cruise ship, are analysed in the following paragraph, considering four simulations as those proposed for this first case study.

4.5.2 Cruise ship

The cruise ship has already been presented in paragraph *4.4.2*. Also for this ship, the four simulations reported in Table 26 are performed and their results summarized and analysed. First, the base line conditions for this case study are proposed again in order to allow a better comparison with the results obtained from the proposed formulation.

- <u>Base line condition:</u>

Considering the design scheduling reported in Table 25, together with the cost of the fuel set equal to 660 $/t, the Mission Costs (MC) results equal to 4665400 $. This cost is to be considered in addition to the monthly IC for the six diesel generators, resulting in a monthly Total Cost (TC) of 4765000 $. These base line costs are summarized in Table 41.

TABLE 41 – BASE LINE COSTS FOR THE CRUISE SHIP

Mission cost MC [k$]	**Installation cost IC [k$]**	**Total cost TC [k$]**
4665.4	99.62	4765

This may be considered as a baseline condition (i.e. to allow a comparison between the proposed approaches) in the following analysis. It is to be highlighted that, the time horizons for each ship operative scenario have been keep constant in each simulation. The optimization problem is solved considering six diesel generators of the same sizes (e.g. homogeneous) or with two possible different sizes (e.g. heterogeneous). In order to compare results from the deterministic and probabilistic approaches to EPLA, the optimum problem is here solved for both the methods. In this perspective, in Table 42, the modal values obtained applying the stochastic approach to EPLA to the case study are proposed for each ship operative scenario under exam.

TABLE 42 - MODAL VALUES FROM THE PROBABILISTIC EPLA FOR THE CRUISE SHIP

Parameter	**Shore**	**Man.**	**Cruising 10kn**	**Cruising 20kn**	**Cruising Max**
Modal values [kW]	9156	10600	14360	17750	31630

The optimal size and scheduling of the diesel generators, considering the ship's main operative condition are proposed and commented together with the resulting costs (e.g. installation and management costs).

- <u>Simulation A:</u>

As specified in Table 26, simulation A considers as inputs the information obtained by the deterministic approach to EPLA. The optimum sizing obtained with this input conditions and considering homogeneous sizes for the diesel generators are six generators sized 10.8 Mw each, as reported in Table 43.

TABLE 43 – DIESEL GENERATOR SIZES AND TOTAL POWER ISTALLED, SIMULATION A AND CRUISE SHIP

Diesel generator	**Rated power [MW]**	**Total power installed [MW]**	**Difference with the base line [MW]**
G1	10.8	64.8	10.8
G2	10.8		
G3	10.8		
G4	10.8		
G5	10.8		
G6	10.8		

Resulting scheduling and loading conditions for the six diesel generators are proposed in Table 44, where are reported the generators (G) that must be switched on in each operative condition. Furthermore, the generators loading conditions (GLF) in percentage of their rated power (i.e. dispatch problem) and their specific fuel oil consumption (SFOC) are also proposed.

TABLE 44 – RESULTS YIELDED BY APPLYING THE DETERMINISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE CRUISE SHIP

	Shore	**Man.**	**Cruising 10kn**	**Cruising 20kn**	**Cruising Max**
DG Sched.	G1-G3	G1-G3-G5-G6	G1-G2-G3-G4-G5	G1-G2-G3- G5	G1-G3-G4-G5-G6
GLF [%]	83.0	76.9	57.8	86.1	79.9
SFOC [g/kWh]	212.9	217.7	217.7	210.9	215.3

The monthly mission cost resulting from this simulation MC are equal to 3601721 $, the IC to 89581 $ with a TC of 3691301 $ per month. The total saving is pointed out by this solution are close to 1073700 $ per month (i.e. which corresponds to more than 12 million dollars per year), as reported in Table 45.

TABLE 45 – COSTS AND SAVINGS ANALYSIS FOR THE DETERMINISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE CRUISE SHIP

MC [k$]	**IC [k$]**	**TC [k$]**	**Savings Monthly [k$]**	**Savings Yearly [k$]**	**Savings Percentage [%]**
3601.7	89.6	3691.3	1073.7	12884.4	22.5

- <u>Simulation B:</u>

In simulation B the same information used in simulation A are considered. On the other hand, heterogeneous sizes of the diesel generators are allowed by deactivating the constraint proposed in equation *(75)*. The optimal solution for the sizing of the power generation system considers three generators of 8.91 MW and other three generators of 11.2 MW, as proposed in Table 46.

TABLE 46 – DIESEL GENERATOR SIZES AND TOTAL POWER ISTALLED, SIMULATION A AND CRUISE SHIP

Diesel generator	**Rated power [MW]**	**Total power installed [MW]**	**Difference with the base line [MW]**
G1	8.91	60.33	15.27
G2	8.91		
G3	8.91		
G4	11.2		
G5	11.2		
G6	11.2		

The total power installed for the power generation system is equal to 60.33 Mw, with a reduction of more than 15 MW (e.g. the 20 percent of the total power installed in design conditions). In Table 47, solution to the scheduling and optimum loading conditions for the diesel generators is proposed.

The monthly mission costs are equal to 3544658 $, instead, the monthly installation cost are 84735 $ and the corresponding total monthly cost for the ship are equal to 3629392 $.

TABLE 47 - RESULTS YIELDED BY APPLYING THE DETERMINISTIC APPROACH TO EPLA WITH HETEROGENEOUS SIZES FOR THE CRUISE SHIP

	Shore	**Man.**	**Cruising 10kn**	**Cruising 20kn**	**Cruising Max**
DG Sched.	G1-G4	G1-G2-G3-G6	G2-G3-G4-G6	G1-G4-G5-G6	G1-G2-G3-G4-G6
GLF [%]	89.1	87.6	77.6	87.5	87.8
SFOC [g/kWh]	210.1	210.4	217.9	210.4	210.3

Possible saving close to 24% compared to the total design costs is highlighted, corresponding to a saving monthly saving of more than 1.1 million dollars and over 13 million dollars per year, as proposed in Table 48.

TABLE 48 – COSTS AND SAVINGS ANALYSIS FOR THE DETERMINISTIC APPROACH TO EPLA WITH HETEROGENEOUS SIZES FOR THE CRUISE SHIP

MC [k$]	**IC [k$]**	**TC [k$]**	**Savings Monthly [k$]**	**Savings Yearly [k$]**	**Savings Percentage [%]**
3544.6	84.7	3629.4	1135.6 $	13627.3	23.8

- Simulation C:

Simulation C is the first simulation performed for this case study that considers as inputs the results obtained applying the stochastic approach to EPLA (i.e. reported in Table 42).

The optimal sizing obtained applying this algorithm to the case study, considering homogeneous sizes for the diesel generators, is proposed in Table 49. It is to be noted that, six generators sized 9.37 MW with a total power installed of 56.22 MW are selected. This, result in a power saving of 19.38 MW.

The solution to the optimum scheduling and dispatch for the diesel generators is proposed in Table 50.

This solution leads to monthly mission cost, installation cost for the diesel generators and total monthly cost equal to 2247509 $, 80610 $ and 2328119 $, respectively.

TABLE 49 – DIESEL GENERATOR SIZES AND TOTAL POWER ISTALLED, SIMULATION C AND CRUISE SHIP

Diesel generator	Rated power [MW]	Total power installed [MW]	Difference with the base line [MW]
G1	9.37	56.22	19.38
G2	9.37		
G3	9.37		
G4	9.37		
G5	9.37		
G6	9.37		

The possible monthly saving is close to 2436881 $ corresponding to 29.2 million dollars per year, as reported in Table 51.

TABLE 50 - RESULTS YIELDED BY APPLYING THE PROBABILISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE CRUISE SHIP

	Shore	**Man.**	**Cruising 10kn**	**Cruising 20kn**	**Cruising Max**
DG Sched.	G3-G4	G1-G5	G2-G5	G1-G2-G5	G1-G2-G4-G6
GLF [%]	48.9	56.5	76.6	63.1	84.4
SFOC [g/kWh]	298.7	287.7	259.4	277.1	255.6

TABLE 51 – COSTS AND SAVINGS ANALYSIS FOR THE DETERMINISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE CRUISE SHIP

MC [k$]	**IC [k$]**	**TC [k$]**	**Savings Monthly [k$]**	**Savings Yearly [k$]**	**Savings Percentage [%]**
2247.5	80.6	2328.1	2436.8	29200	48.9

These are extremely significant savings lead by the combination between the probabilistic approach to EPLA, which seems to guarantee a more efficient prediction of the total operating load, and the optimum algorithm, which is able to minimize management cost related to the fuel oil consumption and installation cost for the diesel generators.

- <u>Simulation D:</u>

Last simulation, adopts as input the same of simulation C but, on the other hand, allows heterogeneous sizes of the generators. The optimum sizing in this simulation select three diesel generators rated 8.91 MW and other three rated 9.6 MW, as proposed in Table 52.

It should be highlighted that the size of these DGs are very similar, despite other cases where the sizes were completely different. This is mainly due to the fact that the optimum sizing of the DGs for this case study is the one proposed in Simulation C. In Simulation D, on the other hand, the problem is forced to select two different sizes for the generators, with the result that the sizes are very similar and close to the optimal one.

Moreover, the total power installed for the power generation system is equal to 55.53 MW, with a noteworthy reduction compared to the design condition.

TABLE 52 – DIESEL GENERATOR SIZES AND TOTAL POWER ISTALLED, SIMULATION D AND CRUISE SHIP

Diesel generator	**Rated power [MW]**	**Total power installed [MW]**	**Difference with the base line [MW]**
G1	8.91	55.53	20.07
G2	8.91		
G3	8.91		
G4	9.6		
G5	9.6		
G6	9.6		

The solutions to the scheduling and dispatch problems are proposed in Table 53. It is to be noted that is decreased the total number of diesel generators online in each scenario, compared to the other simulations.

TABLE 53 - RESULTS YIELDED BY APPLYING THE PROBABILISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE CRUISE SHIP

	Shore	**Man.**	**Cruising 10kn**	**Cruising 20kn**	**Cruising Max**
DG Sched.	G2-G3	G4-G6	G1-G2	G1-G2-G3	G1-G2-G3-G5
GLF [%]	48.9	55.2	76.6	63.1	83.9

SFOC [g/kWh]	298.7	289.9	259.4	257.0	255.7

The resulting monthly mission, installation and total costs are equal to 2241926 $, 79825 $ and 2321751 $, respectively. This allows a reduction in costs of 2443249 $ per month and close to 29.3 million dollars per year, as summarized in Table 54.

TABLE 54 – COSTS AND SAVINGS ANALYSIS FOR THE DETERMINISTIC APPROACH TO EPLA WITH HOMOGENEOUS SIZES FOR THE CRUISE SHIP

MC [k$]	**IC [k$]**	**TC [k$]**	**Savings Monthly [k$]**	**Savings Yearly [k$]**	**Savings Percentage [%]**
2241.9	79.8 $	2321.7	2443.2	29300	51.3

These results highlight the effectiveness of a power fractioning respect to adopt generators of the same size. In fact, in each simulation with heterogeneous sizes, the total cost are lower than in the same conditions considering generators with a homogeneous sizing.

4.5.3 Results summary

The reductions in the power installed revealed in each simulation have some important benefits in terms of weight, complexity of the system, installation costs and greenhouse gas emissions (GHG) reduction. As result of these analyses, the best possible solution (i.e. in cost perspective) is the one with a probabilistic approach to EPLA and heterogeneous size of the generators.

An overview of all the simulation and their results are here proposed in Table 55 and Table 56, for the bulk carrier and cruise ship, respectively.

TABLE 55 –SAVINGS COMPARISON, FOR THE BULK CARRIER

Simulation	Base line [$]	A [$]	B [$]	C [$]	D [$]
Base line [$]	-	18587	20289	30510	32300
A [$]	18587	-	1702	11923	13713
B [$]	20289	1702	-	10221	12011
C [$]	30510	11923	10221	-	1790
D [$]	32300	13713	12011	1790	-

TABLE 56 –SAVINGS COMPARISON, FOR THE CRUISE SHIP

Simulation	Base line [k$]	A [k$]	B [k$]	C [k$]	D [k$]
Base line [k$]	-	1074	1135	2436	2443
A [k$]	1074	-	61.9	1363	1369
B [k$]	1135	61.9	-	1301	1307
C [k$]	2436	1363	1301	-	6.37
D [k$]	2443	1369	1307	6.37	-

4.6 Conclusions

Due to the large development of full electric solutions for power generation and delivery on board ships, the need of an innovative and more effective approach to load prediction in design phase and during the operational life of the ships has been highlighted.

A probabilistic approach for prediction of the total operating load has been applied to the case studies and compared with the traditional deterministic approach performing the optimum algorithm formulated in this chapter to select generator's size, scheduling and loading conditions. The results show possible savings close to the 40% and 50% in a total cost perspective, for the bulk carrier and the cruise, respectively. Moreover, a significant reduction in the total power installed for the power generation system is pointed out, equal to 46% and 26.5% for the bulk carrier and the cruise ships. This reduction has benefits in terms of GHG emissions, installation costs, volume and weight for the power generation system.

In conclusion, it is possible to state that, the combination of the probabilistic approach to EPLA, presented in chapter 3, and the optimum algorithm to size and schedule diesel generators, presented in this chapter, allow designers to efficiently predict the total operating load and minimize (e.g. at design phase) the management and installation costs for a shipboard power generation system, which results more efficient, flexible and reliable.

5 SHIPBOARD ENERGY STORAGE SYSTEMS OPTIMAL SELECTION, SIZING AND MANAGEMENT

The recent worldwide effort on the environmental issue has led to new regulations on greenhouse GA emissions (GHG), both for land and marine applications. Nowadays, the extensive electrification of transportation systems is a promising choice for this purpose. In this perspective, in order to reduce fuel consumption, GHG emission and management costs for a shipboard power generation system, an algorithm for the optimum size and management of an energy storage system (ESS) is proposed in this chapter. This algorithm is tested on two case studies, a ferry and a platform supply vessel (PSV). Information about the total power generated and the power demanded by the propulsion system are available from the on-board integrated automation systems (IAS).

The results yielded from the algorithm show remarkable savings both in a mission perspective and along the whole ship's life, i.e. between 6% and 32% for the ferry and the PSV, respectively. These results prove that an optimal size and management of an energy storage system can lead to disruptive results for shipboard power systems.

5.1 Context

The recent interest on the environmental issue has led to increasingly stringent regulations on greenhouse GA (GHG) emissions due to human activities. The maritime transport of goods accounts for more than 70% of the world trade in terms of value and 80% in terms of volume [123], [124]. According with recent studies, the international shipping emitted in 2012 about 796 million tonnes of CO_2, which is close to 2.2% of the total emission for that year [125], [126]. However, the mid-term forecasting shown that by 2050, a grown between 50% and 250% in CO_2 emissions is possible, depending on the future economic growth and energy development. In this context, also being one of the major human activities, it seems to be possible to achieve a significant environmental impact reduction of the international shipping. For this purpose, energy efficiency has become a key topic in everyday human life in a perspective of optimizing energy consumption. However, it is to be noted that energy efficiency does not mean renouncing a service in order to save energy [127]. It rather means to use less energy to provide the same service. In the perspective of reducing the vessel's environmental footprint and the waste of energy, already since 1983, the International Maritime Organization (IMO) has released regulations in order to minimize pollutant emissions [128]. Nevertheless, it is only since 2011, with the *62nd* session of the IMO's Maritime Environmental Protection Committee (MEPC) that stringent mandatory measures have been adopted to reduce emissions of GHGs from both new buildings and already operating ships [129]. These measures include the introduction of an energy efficiency design index (EEDI) for new ships. This index requires increasingly stringent constraints on GHG emissions from 2013 to 2025, where the target will be to reduce at least of the 30% actual air pollutant emissions [130].

Several areas of action have been identified to improve the shipboard energy performances in design phase, such as hull forms optimization, the introduction of energy-saving devices, structural optimization, light weight constructions and fuel efficiency strategies for ships in service [131], [132]. On the other hand, considering already operating ships, these are subject to a ship energy efficiency management plan (SEEMP), which controls and optimizes their energy management through a performances monitoring system [133]. These rules have encouraged all stakeholders in maritime field to adopt innovative solutions to improve ship's efficiency. As a result, there are significant reductions in fuel consumption, utility costs and air pollution.

Nowadays, the extensive electrification of transportation systems (e.g. cars, trains, airplanes and ships) has become an appealing technology compared to the conventional concepts, even for marine applications. In this perspective, the widely known All-Electric Ship (AES) solution, presents a large variety of devices, technologies and operating strategies that could lead to a more flexible, efficient and sustainable design and management of ships, [134]-[137]. In fact, many technologies and practices adopted in recent years in shore applications can also be beneficial in marine field [138]. Technologies such as energy storage systems (ESS), variable frequency drives (VFDs) and approaches as unit commitment (UC), power system dispatch (PSD) and demand side management (DSM) have been barely introduced in most cases, [139]-[143].

It is to be highlighted that, a key aspect of all these technologies, is the knowledge the ability to predict the load power behaviour. However, almost each ship presents a different load profile. This is essentially due to the large amount of power installed for the propulsion system, which power demand can varies significantly in relation to the weather conditions encountered or the speed desired. In the context of AES, where both the propulsion and the hotel loads are powered by electricity, this high variation in power demand is even more significant. In fact, in those conditions, diesel generators (DGs) often work far from their optimal working point. As a result, an increase in costs, fuel consumption and emissions is pointed out. Therefore, as it happens in many land application where there are uncertainties related to the power generation profile due to weather conditions (e.g. wind and solar power generation plant), also on board many vessels may be advantageous to install energy storage systems. Such systems can be used in order to cover the fluctuating load variations and increase the whole power system efficiency, reliability and flexibility [144].

5.2 Literature review

In literature, several works have addressed the problem of the optimum management of the power generation system on board ships. In [145], three different power plant configurations are proposed for each case study, together with two possible algorithms for an Energy Management System (EMS), i.e. the first based on an optimization problem and the second on a decision logic approach. However, its results do not provide the optimal size for the ESS, which it is chosen *"a priori"*. Another research [146], focused on marine power management systems proposes an optimization of the load dependent start-ups table for DGs in order to minimize fuel consumption and prevent from blackout conditions, without considering the installation of an ESS.

In [147], an EMS is developed based on bond graph models in conjunction with a particle swarm optimization (PSO) algorithm. This method optimizes the power system's configuration under actual data. However, also in this work, the ESS best size selection is not investigated but selected "*a priori*".

In [148], another work on ESS on board ships is proposed. In this work, a discrete-time Markov decision process (MDP) is formulated in order to solve the problem of the optimum power generation scheduling. Unfortunately, even if it considers the installation of an ESS and its best size, it does not explain how the best size can be determined.

The work proposed in [149] formulates a dynamic dispatch problem for a ferry to find the optimal loading strategy for the on board generators, considering also the presence of an ESS. The best size for this energy storage unit is determined with an numerical "*brutal force*" method.

In [150], authors describe an approach to evaluate the impact of energy storage modules sizing and location for ship's survivability and quality of service (QoS). Basically, a multi-objective optimization algorithm (i.e. the multi-objective particle swarm optimization) is used to obtain a Pareto optimal solutions considering QoS and survivability, instead of the optimum management or size selection of the ESS.

On the other hand, aim of this chapter is to propose an approach to optimal sizing, select and manage an ESS (e.g. battery, flywheel or super-capacitor) based on the knowledge of power load profile. In fact, these problems can not be separated and the optimal sizing is strictly related to the optimum management of the power generation system. Therefore, in order to properly select the optimal ESS size, DGs should work as close as possible to their most efficient loading condition. Furthermore, the ESS dynamic behaviour should guarantee an acceptable life duration of the system itself. Here, these optimum problems are decomposed into two main algorithms (i.e. as shown in Figure 63). The first algorithm searches the best size for the ESS. The second one, on the other hand, solves the problem of finding the best dynamic dispatch of both the DGs and the ESS. The best sizing is defined considering as objective function the sum of the power system management cost (e.g. fuel oil consumption derived into the dynamic dispatch problem), installation and replacement costs for the ESS and the inverter.

This method also considers the optimum management of the ESS in reference to both its life expectation and the number of replacements along the whole ship's life (i.e. usually 25 years).

5.3 Problem statement

As already stated, the problem of finding the optimum size for an energy storage system is strictly related to the dispatch and scheduling for the DGs and the energy storage modules (ESM). In fact, in order to find the optimal size of the storage, it is required to know the optimum scheduling and dispatch for the whole power generation system.

The whole problem of selecting the optimal size for an ESS and obtain the optimum scheduling and dispatch for the power generation system is a very complicated issue. In fact, it involves a large number of variables, parameters and information.

As proposed in the first paragraph (e.g. literature review), there are methods that cover only part of these problems [145]-[150]. The method proposed in this thesis, instead, is focused on the possibility of globally solve the problem finding a satisfactory compromise between accuracy of results and calculation time. Therefore, an algorithm for the energy management system (EMS) is developed and proposed. In this context, the EMS has the objective to find the optimum scheduling and dispatch for the power generation system. It is to be noted that, the main difference between an EMS and a power management system (PMS), is that the PMS works with very short time steps in order to stabilize the ratio between voltage (V) and frequency (f) for the power system. The PMS also balances the power demanded and the generation. On the other hand, the EMS works with wider time steps, considering events in the past, in the present and performing forecasts on the future.

In the perspective of selecting the optimal size of an ESS, the results obtained by the EMS are extremely useful information, indeed. Actually, a different size of the storage means a different performance for the whole power generation system and a different management strategy, as well. This is confirmed considering both a short-term horizon (e.g. a mission time horizon) and a long-term horizon (e.g. five years or the ship life).

Typical outputs from the EMS are the energy exchanged by the storage, the number of charging and discharging cycles in the time horizon, the state of charge (SoC), the power delivered by generators and their consumption. These outcomes, combined with the input data (e.g. load power, power system characteristics and ship operating conditions) allow to optimally select the size of the storage system and other key features (e.g. which technology to adopt and its main characteristics). Nevertheless, if the problem of finding the best size of an ESS is globally considered, it should be formulated applying a mixed-integer non-linear programming (MINLP). In fact, it involves both integer (e.g. the generator's start-up and shutdown states) and continuous variables (e.g. the power delivered by the generators or exchanged by the ESS). Moreover, it is to be note that this variables should be multiplied by each other in the objective function and, sometimes, in some constraints.

Due to the product between variables (e.g. the power exchanged by the ESS and its state of charge), the problem become non-linear [151]. Such a formulation requires a very expensive computational time, which do not ensure a more accurate result compared with other formulations. For this reason, the entire problem has been decomposed into two main sub-problems, as shown in Figure 63. The first sub-problem should solve the ESS optimal selection and sizing (e.g. in orange in Figure 63). This problem provides important information used as inputs for the second one. This former sub-problem (e.g. in blue in Figure 63), has three objectives: finding the optimal scheduling, dynamic dispatch for the DGs as well as finding the optimal management for the ESS (e.g. proposed in green in Figure 63)

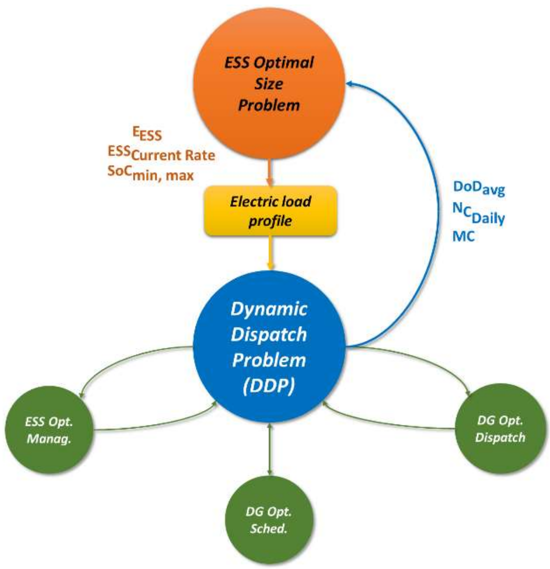


Figure 63-Main problem decomposition

5.4 Energy storage system optimum sizing, problem formulation

The dynamic dispatch problem for the power generation system has been developed in General Algebraic Modeling System (GAMS) environment. On the other hand, MATLAB has been used in order to optimize the size of the ESS considering the outcomes obtained in GAMS. Therefore, according to paragraph 5.3, the global problem has been divided into the ESS optimal size selection and the dynamic dispatch (e.g. for the DGs and the ESS) problems.

In this paragraph, an algorithm that solves the problem of the optimal sizing of the ESS is formulated and proposed. Due to the non-convexity of the problems, multiple searches over the feasibility space have been performed.

In addition to the optimal sizing of the ESS, this algorithm provides useful information on the storage system. These information are used as inputs to the other sub-problem, as it is highlighted in Figure 63. This problem is formulated with a non-linear programming (NLP) approach.

5.4.1 Problem's input

Main inputs of the problem are the characteristics of the storage system. These, depend on the technology selected (e.g. battery, flywheel or super capacitor). In this approach, they can be changed in order to allow comparison between different storage technologies.

The main information are the technology selected, the rated current in charge C_c and discharge mode C_d, the maximum depth of discharge allowed DoD, the rated power in charge P_{ESSc} and discharge P_{ESSd}, the maximum E_{ESSmax} and minimum E_{ESSmin} size for the storage. Furthermore, other inputs are the initial state of charge SoC_0 and the final state of charge SoC_f, the nominal cost per kWh of the storage system C_{inst} and the relation between the DoD and the number of charge and discharge cycles $N_{C_{Tot}}$ guaranteed in the ESS life.

5.4.2 Variable of the problem

The only variable of this sub-problem is continuous and identifies the size of the energy storage system (E_{ESSnom}). The solver selected in order to perform this optimization in MATLAB is *"fmincon"*. This solver is able to find a solution for NLP problems and it requires, as input, the starting point for the research.

5.4.3 Objective function

The objective function accounts for the total cost TC calculated as the sum of the installation (e.g. for the ESS and the inverter) and replacement costs IC (e.g. of the ESS), i.e. considering both the cost for the first installation and the future replacements, and the management costs MC for the power generation system. These costs are calculated over the ship's life horizon (e.g. usually considered 25 years), as reported in equation *(80)*.

$$TC = IC + MC \tag{80}$$

Where, IC is the sum of installation costs C_I and replacement costs C_R. Therefore, the installation costs C_I are calculated as the sum of the energy storage $\mathrm{C_{I_{ESS}}}$ and the inverter installation costs $\mathrm{C_{I_{INV}}}$, as proposed in equations *(81)-(83)*.

$$C_I = C_{I_{ESS}} + C_{I_{INV}} \tag{81}$$

$$C_{I_{ESS}} = \gamma \cdot E_{ESS_{nom}} \tag{82}$$

The first is proportional (γ) to the product of the nominal cost of the storage $C_{inst_{ESS}}$ and its nominal size E_{ESS}. The latter, instead, is a function of the nominal cost of the inverter $C_{inst_{INV}}$, (i.e. a piece-wise linear function of the inverter size) and its nominal power P_{INV}, as proposed in equation *(83)*. Where β_1 and β_2 are coefficients of nominal cost for the inverter depending on the rated power. Combining equations *(81)-(83)*, it is possible to formulate the installation costs as proposed in equation *(84)*.

$$C_{I_{INV}} = \begin{cases} \beta_1 \cdot \left(P_{INV}' - P_{INV}\right) & if\, P_{INV} \leq P_{INV}' \\ \beta_2 \cdot \left(P_{INV} - P_{INV}'\right) & if\, P_{INV} > P_{INV}' \end{cases} \tag{83}$$

$$C_I = C_{inst_{ESS}} \cdot E_{ESS} + C_{inst_{INV}} \cdot P_{INV} \tag{84}$$

On the other hand, the costs related to the replacement of the storage system (C_R) along the whole ship's life are strictly related to the storage main features (e.g. the number of cycles $N_{C_{Tot}}$ guaranteed in function of the depth of discharge DoD) and the management strategy applied (i.e. which is a result of the second sub-problem on the dynamic dispatch for the power generation system), as proposed in equation *(85)*.

$$C_R = C_{inst_{ESS}} \cdot E_{ESS} \cdot N_{replacement} \tag{85}$$

It is to be noted that, into the replacement costs, are omitted the costs due to the inverter replacements. This is due to the fact that the inverter will not be replaced, being the size and mean features of the storage always the same.

The number of replacements for the storage system ($N_{replacement}$) are defined combining outputs from the dynamic dispatch sub-problem and variables of this optimization problem (i.e. optimal size for the ESS), as obtained in *(89)* combining equations *(86)-(88)*.

$$N_{C_{Daily}} = \frac{E_{exchanged}}{2 \cdot E_{ESS}} \tag{86}$$

$$N_{C_{Tot}} = a \cdot e^{\left(b \cdot DoD_{avg}\right)} + c \cdot e^{\left(d \cdot DoD_{avg}\right)} \tag{87}$$

$$N_{Service_{Daysy}} = \frac{N_{C_{Tot}}}{N_{C_{Daily}}} \tag{88}$$

Where, $N_{C_{Daily}}$ are the total number of daily charge/discharge cycles of the storage system, $E_{exchanged}$ is the total energy exchanged by the ESS in the mission, $N_{C_{Tot}}$ are the total number of cycles guaranteed by the manufacturer along the ESS's life, DoD_{avg} is the average *DoD* performed in the mission and $N_{Service_{Daysy}}$ is the potential number of service days for the ESS. Therefore, it is possible to state that equation *(88)* can be considered as an aging effect on the total life of the ESS. In fact, the higher is the number of daily cycles the shorter will be the total life of the storage system. Moreover, the higher is the DoD_{avg}, again the shorter will be the life og the ESS.

Finally, for what concern the installation costs, it is to be noted that in equation *(89)*, the numerator represents the total number of days in the whole ship's life, which is 25 years, traditionally.

$$N_{replacement} = \frac{25 \cdot 365}{N_{Service_{Daysy}}} \tag{89}$$

The management costs *MC* are calculated according with the outputs of the dynamic dispatch problem. These, account for those costs related to the DG's fuel oil consumption, as proposed in equation *(90)*.

$$\mathrm{MC} = \sum_{i,j=1}^{G,S} \left\{ \alpha \cdot \mathrm{P}_{\mathrm{gen}_{ij}} \cdot \mathrm{SFOC}_{ij} \cdot \mathrm{FC} \cdot \mathrm{dt} \right\} \tag{90}$$

Where, $P_{gen_{ij}}$ and $SFOC_{ij}$ are the power delivered and the specific fuel oil consumption (e.g. in g/kWh) for the i^{th} generator at the j^{th} time step, respectively. Furthermore, *FC* is the cost per unit of the fuel oil (e.g. in \$/t) and α is a constant equal to 10^6 adopted to convert fuel oil grams to tons, *G* is the total number of DGs installed, *dt* is the simulation time frame considered and *S* the total number of time instances.

5.5 Power generation system dynamic dispatch and scheduling, problem formulation

In this sub-problem, the algorithm for the EMS is formulated as an optimization problem in which the main variables are the state of the DGs, the power delivered by each DG and by the ESS. In this perspective, it is possible to state that this problem solves three main sub-problems (e.g. the scheduling for the DGs, their dispatchment and the ESS optimum working point), as proposed in Figure 63. Involving both integer and continuous variables, this dynamic dispatch problem (DDP) is formulated adopting a mixed-integer linear programming (MILP) algorithm.

Such approach, guarantees acceptable calculation time and good accuracy of the solution. The results must guarantee the best scheduling and dispatch for the power generation system according to the objective function and constraints adopted.

This algorithm has been formulated in GAMS environment, adopting CPLEX as a solver for the optimization problem and Matlab as interface between inputs and outputs.

5.5.1 Input to the dynamic dispatch problem

Inputs of the DDP are all the main information about the ESS, such as size, rated power in charge and discharge, initial state of charge, maximum depth of discharge and current rate. Moreover, information about the DGs are also required. These inputs are the total number *G* of diesel generators installed, their rated power $P_{G\,rated_i}$, minimum $DG_{min_{up}}$ time up or down $DG_{min_{down}}$ and the simulation time step *dt*. All these inputs are summarized in Table 57.

5.5.2 Problem's variables

Variables of this problem are the power delivered by the i^{th} generator at the j^{th} time step of the simulation $P_{gen_{ij}}$, the i^{th} generator's state at the j^{th} time step, two auxiliary variables v_{ij} and w_{ij} accounting for the start-up and shutdown conditions, respectively. Furthermore, other variables are the power delivered/absorbed by the ESS (i.e. depending on the sign) $\mathrm{P_{ESS_j}}$ and the state of charge $\mathrm{SoC_j}$ of the ESS at the j^{th} time step. As it happens for the inputs, also these variables and their symbols are summarized in Table 57.

TABLE 57 - DDP INPUTS AND VARIABLES

Parameter	Symbol
Inputs:	
ESS rated power in discharge [kW]	$\mathrm{P_{ESS_d}}$
ESS rated power in charge [kW]	P_{ESS_c}
ESS initial state of charge [%]	SoC_0
ESS final state of charge [%]	$\mathrm{SoC_f}$
ESS maximum depth of discharge [%]	DoD_{max}
ESS current rate	C
Number of DGs	G
Number of simulation time steps	S
Simulation time step [s]	dt
DG's rated power [kW]	$\mathrm{P_{G\ rated_i}}$
DG minimum time down [min]	$DG_{min_{down}}$
DG minimum time up [min]	$\mathrm{DG_{min_{up}}}$
Variables:	
DG power delivered [kW]	$P_{gen_{ij}}$
DG start-up state	v_{ij}
DG shutdown state	w_{ij}
ESS power exchanged [kW]	$\mathrm{P_{ESS_j}}$
ESS state of charge [%]	$\mathrm{SoC_j}$

5.5.3 Objective function

The objective function considers the minimum number of starts and stops, the minimum power delivered by generators, their best possible loading condition and the best management for the ESS.

In this perspective, the first term in equation *(91)* accounts for the power delivered $P_{gen_{ij}}$ by the i^{th} generator in the j^{th} time step and it is multiplied by the weight $\mathrm{w}_{\mathrm{P}_{\mathrm{gen}}}$ in order to allow a normalization of all the terms of the function.

The second term, on the other hand, identifies the state v_{ij} of the i^{th} generator in the j^{th} time step. This is used, together with its weight w_{Su}, in order to evaluate and control the total number of start-ups for DGs. The loading conditions for the DGs are considered in accordance with the penalty function LF_{n} that tries to load the DGs in the most efficiency way.

This penalty function has been modeled as a piece-wise linear function and follows the behaviour of the specific fuel oil consumption curve of the DGs, as proposed in equations *(92)-(96)*. As it happens for each term of the objective function, also this one is multiplied by its weight w_{LF} in order to control its global relevance.

Finally, the last term accounts for the management of the ESS. Specifically, it considers the mean state of charge in the simulation multiplied by its weight w_{SoC}.

The signs of the function are chosen according with the aim of this problem, which is to minimize the fuel oil consumption and guarantee the best management for the ESS (i.e. combining the best management of DGs and preservation of the ESS's life duration).

$$J_{objective} = \min_{P_{gen_{ij}},\, v_{ij},\, w_{ij},\, SoC_j} \left\{ w_{P_{gen}} \cdot \sum_{ij} P_{gen_{ij}} + w_{S_u} \cdot \sum_{ij} v_{ij} + w_{LF} \cdot \sum_{n} LF_n - w_{SoC} \cdot \sum_{j} \frac{SoC_j \cdot dt}{S} \right\} \quad (91)$$

5.5.4 Penalty function

The penalty function on the loading condition of the DGs is formulated as a piece-wise linear function. The values assumed depend on the values of the *SFOC*, as shown in Figure 64.

To model it in GAMS, the following variables have to be introduced: power delivered by the n^{th} step of the piece-wise linear function $P_{gen_{ijn}}$, that is also depending on the i^{th} diesel generator considered at the j^{th} time step, with $n \in \mathbb{N}$ (i.e. from 1 to N, where N is the total number of linear steps of the function) and v_{ijn}, which identifies the switch from one step to another one of the piece-wise linear function, i.e. as shown in Figure 64.

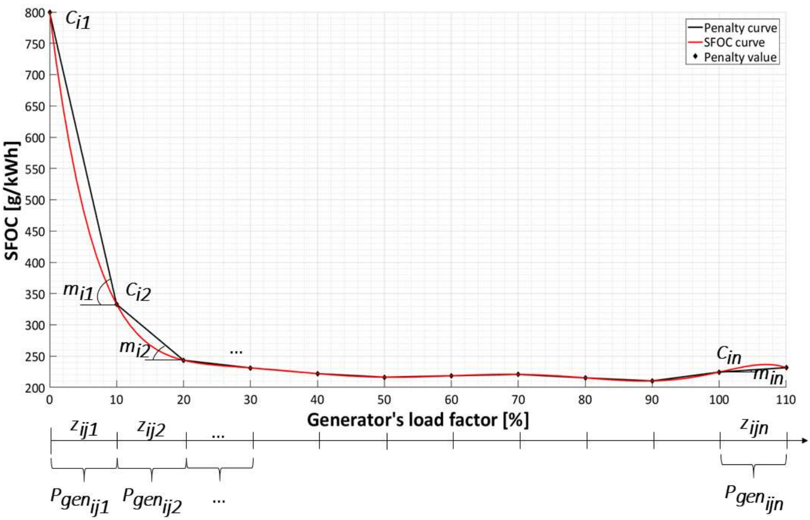


Figure 64-Diesel generator's penalty function on loading conditions

Parameters are also introduced to characterize this function, such as m_{in}, which identifies the angular coefficient of the n^{th} step of the function considering the i^{th} diesel generator, and C_{in} that is the known value in the same condition.

In *(92)*, the total power delivered by the i^{th} diesel generator at the j^{th} time step is defined as the sum between the power delivered by the n^{th} power range, defined by the piece-wise linear function.

$$P_{gen_{ij}} = \sum_{n=1}^{N} P_{gen_{ijn}} \tag{92}$$

Moreover, in equation *(93)* the power limits of each step of the function are defined as P_{nom_n} and equation *(94)* states that it is not possible to work in the $n+1^{th}$ step without working also in the n^{th} one.

$$0 \leq P_{gen_{ijn}} \leq P_{nom_n} \cdot z_{ijn} \tag{93}$$

$$z_{ij(n+1)} \geq z_{ijn} \tag{94}$$

Finally, the corresponding penalty value is proposed in equation *(95)*. Where $P_{g_{\%}}$ has been defined in equation *(96)*.

$$LF_n = \begin{cases} \sum_{i,j=1}^{G,S} \left[C_{in} + m_{in} \cdot P_{g_{\%}} \right] & if\, n=1 \\ \sum_{i,j=1}^{G,S} \left[C_{in} + m_{in} \cdot P_{g_{\%}} - C_{in} \cdot z_{ijn} \right] & if\, n>1 \end{cases} \tag{95}$$

$$P_{g_{\%}} = \frac{P_{gen_{ijn}}}{P_{nom_n}} \tag{96}$$

5.5.5 Auxiliary equations

First auxiliary equation of this optimization problem is equation *(97)*. This considers the dynamic behaviour of the ESS state of charge, which depends on the power delivered or absorbed by the ESS at the j^{th} time steps, on the initial state of charge SoC_0 and on the rated capacity of the storage $E_{ESS_{nom}}$.

$$SoC_j = SoC_0 - \sum_{j=1}^{S} \left[P_{ESS_j} \cdot \frac{dt \cdot 100}{E_{ESS_{nom}} \cdot 3600} \right] \tag{97}$$

Equation *(98)* considers the maximum power absorbed or delivered by the ESS. This, depends on the product between the rated capacity of the storage $E_{ESS_{nom}}$ and the current capacity in charge $C_c \cdot$ and discharge C_d, respectively.

$$P_{ESS_{max}} = \begin{cases} C_d \cdot E_{ESS_{nom}} & \textit{in discharge} \\ C_c \cdot E_{ESS_{nom}} & \textit{in charge} \end{cases} \tag{98}$$

The last auxiliary equation *(99)* accounts for the state (i.e. switched on or off) of the i^{th} generator.

$$u_{i,j-1} - u_{i,j} = w_{i,j} - v_{i,j} \tag{99}$$

In this equation, the difference between the diesel generator's state at the $j\text{-}1^{th}$ time step $u_{i,j-1}$ and at the j^{th} time step $u_{i,j}$ is equal to the difference between the variable $w_{i,j}$, which accounting for the shutdown state, and the variable $v_{i,j}$ accounting for the start-up condition, both considered at the j^{th} time step.

5.5.6 Problem's constraints

Constraints are formulated as linear equality and inequality function.

- Power balance:

The first constraint guarantees the balance between the power demanded and the power supplied at each time step, as proposed in equation *(100)*.

The power supplied by the generation system is equal to the sum of the power supplied by each DG and the power delivered by the ESS. It is to be noted that the power demand is an input information of the problem.

$$\sum_{i=1}^{G} P_{gen_{ij}} + P_{ESS_j} = P_{load_j} \tag{100}$$

- <u>Spinning reserve limit:</u>

On the other hand, the second constraint is formulated in order to guarantee a reasonable reserve of power and to prevent from black-out conditions. In fact, such conditions can be very dangerous in specific ship's operative scenarios (e.g. in dynamic positioning).

This constraint is here named *"spinning reserve"*, even if it does not consider only the spinning sources of power but, rather, also the power from static sources (e.g. such as the batteries). The spinning reserve limit is formulated as proposed in equation *(101)*.

$$\frac{\sum_{i=1}^{G} P_{Grated_i} \cdot u_{ij} + P_{ESS_j} - P_{load_j}}{P_{load_j}} \geq SR_j \tag{101}$$

As already introduced, it is to be noted that in this formulation, also the power available by the ESS in discharge mode $P_{ESS\ max_d}$ is considered as a reserve of power.

One of the main reasons for this different formulation is the need to consider also scenarios where all the generators are turned off at the same time, with all the power demand covered by the ESS. Otherwise, the solver would consider always at least one DG switched on in each time step. In fact, this is in contrast with the aim of this work.

The value of reserve SR_j can be set depending on the operating condition in which the ship is working. In fact, considering for example a supply vessel, this reserve can be increased in order to guarantee a more stringent level of reliability in dynamic positioning (DP) condition rather than in cruising condition [152].

- Diesel generators minimum time up and down:

The minimum time for the DGs to be down and up are guaranteed with the two constraints proposed in equations *(102)* and *(103)*. Where, $DG_{min_{up}}$ and $DG_{min_{down}}$ are the minimum time for DGs to be up and down, respectively, as defined in the inputs.

$$u_{i,j} \geq \sum_{j=1}^{S} DG_{min_{up}} \cdot v_{i,j} \qquad (102)$$

$$1-u_{i,j} \geq \sum_{j=1}^{S} DG_{min_{down}} \cdot w_{i,j} \qquad (103)$$

- Final value of the SoC:

The value of state of charge for the ESS, in the last time step S^{th}, is defined in the inputs and guaranteed by equation *(104)*.

$$\sum_{j=1}^{S} \left[SoC_{j} - SoC_{j-1} \right] = SoC_{f} \qquad (104)$$

- Diesel generator power limits and SoC dynamic limits:

Furthermore, in this problem, bound constraints are formulated in order to model some characteristic of the system, such as: minimum $P_{gen_{min}}$ and maximum $P_{gen_{max}}$ power available from the DGs in equation *(105)*, maximum SoC_{max} and minimum SoC_{min} values for the state of charge of the storage system.

$$P_{gen_{min}} \leq P_{gen_{ij}} \leq P_{gen_{max}} \qquad (105)$$

Where, SoC_{min} is equal to the difference between the maximum state of charge and the maximum depth of charge DoD_{max} of the ESS, as reported on the left side of equation *(106)*.

$$(SoC_{max} - DoD_{max}) \leq SoC_{j} \leq SoC_{max} \qquad (106)$$

- Initial diesel generator states and initial SoC:

Finally, the formulation allows to set the initial state of some variables, which are defined in the problem's inputs. These, are the initial $u_{i,0}$ state for the DGs *(107)* and the initial state of charge SoC_0 of the storage system *(108).*

$$u_{i,j} = u_{i,0}\ for\ j=0 \tag{107}$$

$$SoC_j = SoC_0\ for\ j=0 \tag{108}$$

The following section proposes and describes the case studies, together with the input information adopted in order to test this methodology and allows a comparison with the historical data recorded from the on-board automation systems.

5.6 Case studies

Two ships, with very different load profiles, have been selected as case studies in this work. These are a ferry and a platform supply vessel (PSV). For both the case studies, data have been extracted from the on board integrated automation system (IAS). These data have already been presented and analyzed in details in [145].

However, in order to allow a better comparison between the collected data and the results obtained with the proposed formulation, a brief introduction and analysis both on them and on the main characteristics of the case studies are proposed in this section.

5.6.1 Ferry

Ferries present very stringent scheduled timetables. For this reason, they often present a cyclic behaviour. However, for those designed with an electric propulsion system, the electrical load profile is mainly affected on the power required for the propulsion; which is strongly dependent on the weather conditions and on the cruising speed.

The automation data have been extracted with a frequency of 1 Hz along a whole day of operation, starting at 13:00 PM. Here, only the propulsive load profile and the power delivered by the DGs are available. As a result, the behaviour of the “hotel load” is unknown.

The power generation system presents two fixed speed diesel generators of 1200 kW each and other two of 640 kW. Moreover, this ship presents an electrical propulsion system with two azipod propellers of 1200 kW each.

The main characteristics of this ship are summarized in Table 58.

TABLE 58 – FERRY MAIN PARAMETERS

Parameters	Ferry
Machinery:	
2 x DGs	1200 kW
2 x DGs	640 kW
Propulsion system:	
2 x Azipods	1200 kW
Data set:	
Sampling frequency	1 Hz
Length	24 h

The profile of the power demanded, proposed in Figure 65, shows a cyclic behaviour according with ship's timetables. The demand of propulsive power shows a peak at the third hour of measurements, probably due to a mission delay that has required increasing the speed or due to adverse weather conditions that may cause an increase in the power required to generators in order to maintain the cruising speed and respect timetables.

The power supplied by each diesel generator is also known and shown in Figure 66 and the main characteristics are summarized in Table 59. It is possible to note that the DG1 (e.g. with a rated power of 1200kW) is switched off for the entire measurements horizon. On the other hand, DG2 (i.e. 640 kW) and DG3 (i.e. 1200 kW) are turned on for the most of the period, with a power delivered variable between the 3.3% and the 91.7% for the first (i.e. DG2), and between the 6.3% and the 94.7% for the latter (i.e. DG3). The last diesel generator DG4 (i.e. 640 kW) is turned on in order to cover the peak in demand at the first and third hour into the sampled data horizon.

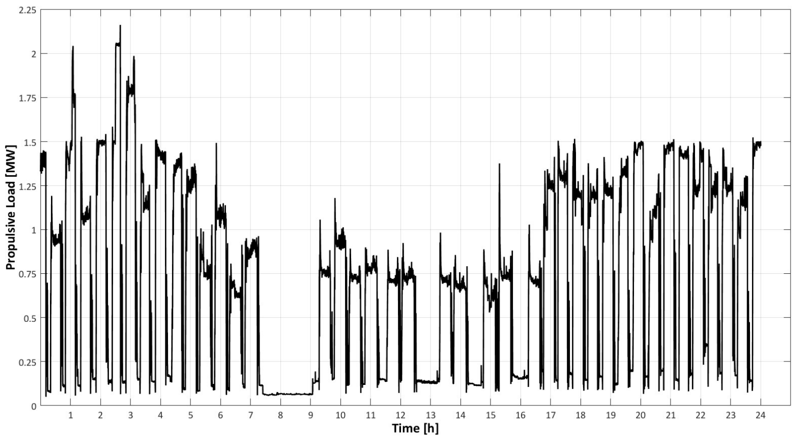


Figure 65-Power demand, Ferry

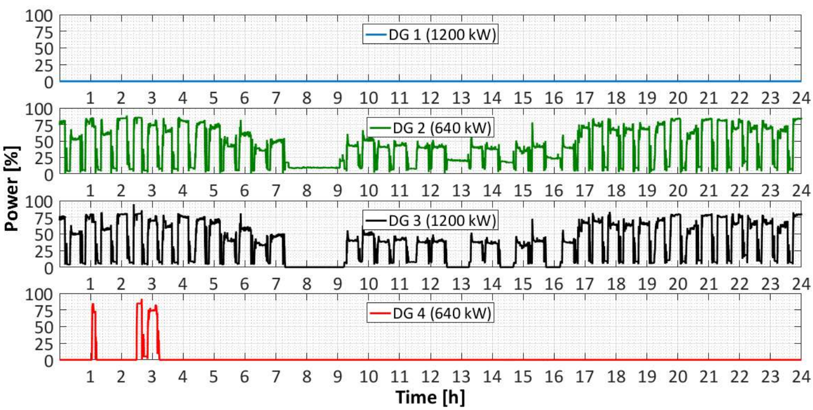


Figure 66-Power delivered by each DG, Ferry

TABLE 59 - DG'S MANAGEMENT FROM DATA, FERRY

Parameter	DG1	DG2	DG3	DG4
Avg load [%]	0	41.1	43.1	55.5
Min. load[%]	0	3.3	3.1	6.3
Max. load[%]	0	88.7	94.7	91.7
Start-ups	0	0	5	2

5.6.2 Platform Supply Vessel

Typical supply vessels provide different services to offshore installations such as oil platforms, wind generators or special installations. PSVs provide special services to oil platforms and wind generators, which require dynamic positioning (DP) capabilities as well as pumping or winching operations. All these operational conditions require a high level of power, together with a high level of reserve of power in order to prevent from very dangerous black out conditions [152]. For these reasons, this kind of ships often work at low loading conditions of the DGs (e.g. close to 30-40%, in order to guarantee a high reserve of power for DP conditions).

Consequently, a high level of fuel consumption is pointed out from the data recorded by the on-board IAS. The power generation system presents four fixed speed DGs, two with a rated power of 2350 kW (i.e. DG1 and DG3) and the others with a rated power of 994 kW (i.e. DG2 and DG4). The propulsion system account of two main azimuth thruster propellers of 2200 kW each and two bow thrusters of 880 kW each.

Finally, also an azimuth bow retractable thruster is installed for dynamic positioning class 3 (DP3) conditions, with a rated power of 880 kW. The main characteristics of this case study are summarized in Table 60. The data have been recorder with a sampling frequency of 0.2 Hz, along a time horizon of almost 6 days.

TABLE 60 – PSV'S MAIN PARAMETERS

Parameters	**PSV**
Machinery:	
2 x DGs	2350 kW
2 x DGs	994 kW
Propulsion system:	
2 x Azipods	2200 kW
2 x Bow thrusters	880 kW
1 Bow retractable thruster	880 kW
Data set:	
Sampling frequency	0.2 Hz
Length	6 days

Information about the total power generated and the power demanded by the propulsion system are available from the IAS.

In this perspective, it is also possible to calculate the amount of power demanded by the auxiliaries and the losses of the system. However, due to the aim of this work, only the total power demanded to the power generation system is of interest and its profile is proposed Figure 67. This shows a non-cyclic behaviour, unlike it happened for the ferry.

Along the data-sampling horizon, there are many peaks due to DP condition, which are mainly affected by adverse weather conditions such as heavy wind, current and waves. Furthermore, there are some periods where the power demand is very low, in comparison to the DP condition. These, are conditions where the ship is *"at Anchor"* to the platforms, i.e. the propulsion system is turned off and the power demand is only due to auxiliaries and air conditioning.

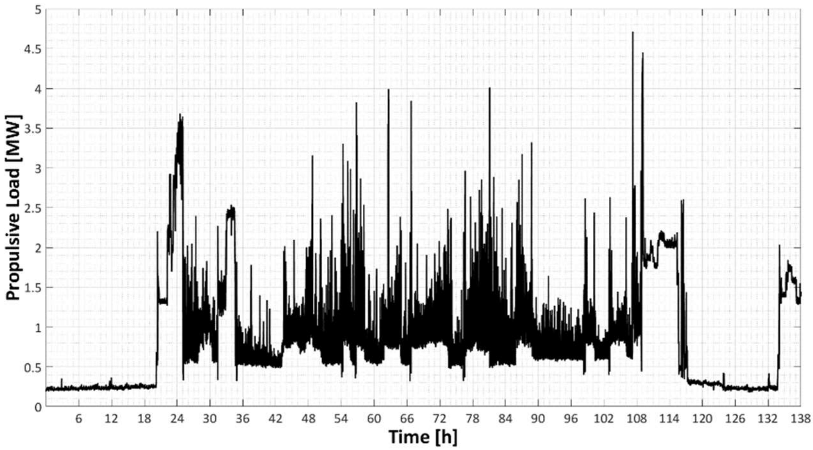


Figure 67-Power demand, PSV

Considering the DGs, the data proposed in Figure 68 shown a different behaviour for each one. These information are summarized in Table 61.

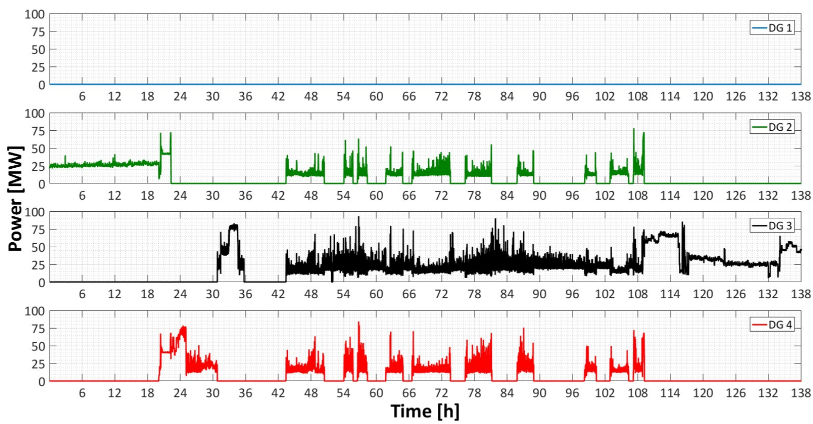


Figure 68-Power delivered by each DG, PSV

TABLE 61 - DG'S MANAGEMENT FROM DATA, PSV

Parameter	DG1	DG2	DG3	DG4
Avg load [%]	38	33.5	37.7	34.8
Min. load[%]	5.9	7.7	5.2	6.1
Max. load[%]	100.4	120.5	101.9	106
Start-ups	34	47	33	38

The first diesel generator DG1 is turned off for the entire time horizon. In fact, it is probably used in extreme adverse weather conditions in order to perform DP3 operations.

The others DGs show very different behaviour, with loading conditions between 1.5% and 84.2% of their rated power. However, the average loading conditions for DG2, DG3 and DG4 are 17.5%, 24.7% and 21.9% of their rated power, respectively.

Therefore, high levels of fuel oil consumption are pointed out from the measurements, resulting in high management costs and GHG emissions.

5.6.3 Problem's inputs

Once the case studies have been described in details, the input information of the optimization problem should be introduced. These information, are summarized (i.e. in Table 62**)** for completeness with the values assumed in order to perform this optimization.

Furthermore, the power required by the generation system for the case studies are those reported in Figure 65 and Figure 68. In addition, the curve considered in this work for the *SFOC* of the fixed speed DGs is the one already proposed in Figure 64.

Finally, it is to be highlighted that, the technology selected as energy storage system in this work is a lithium-ion battery for marine application.

TABLE 62 – PROBLEM'S MAIN INPUTS

Parameters	Ferry	PSV
Researching information:		
Range [kW]	250-1500	500-2500
Starting point [kW]	400	700
Energy storage system main characteristics:		
Nominal current	1C	2C
SoC_0 and SoC_f [%]	70	70
SoC_{min} and SoC_{max} [%]	20-100	20-100
η_{ESS}	98	98
Diesel generator main characteristics:		
$P_{gen_{max}}$ [%]	100	110
$P_{gen_{min}}$ [%]	5	5
$DG_{min_{down}}$ [min]	5	15
$DG_{min_{up}}$ [min]	15	15
DDP objective function's weigths:		
$w_{P_{gen}}$	10^{-6}	10^{-6}
w_{S_u}	15	2
w_{LF}	10^{-2}	1
w_{SoC}	3	20
Power reserve limit:		
SR_j [%]	10	50

5.7 Sensitivity analysis

In order to test the dynamic dispatch algorithm and evaluate its sensibility to different inputs, a sensitivity analysis has been performed for both the case studies. Main parameters of this analysis are the initial and final state of charge of the ESS and its nominal current. Results of this analysis are here proposed and commented.

5.7.1 Ferry

Furthermore, as a result of several tests performed to select the best parameters of the battery system, for this case study, an *"energy intensive"* application was found to be the most advantageous (i.e. the nominal current in charge and discharge is set equal to 1 *C*).

This, even if a *"power intensive"* solution is the best one in a perspective of management cost reduction (i.e. for a battery of the same size with a nominal current in charge and discharge equal to 4 *C*, the mission cost saving is equal to 8% instead of 7.3%, which is the result for the best solution).

This, is mainly due to the different management strategies applied to the storage system in these two applications, which correspond in different costs related to the replacement (C_R) of the storage and for the installation of the inverter (i.e. in the power intensive application, the nominal power P_{INV} of the invert is C^{th} times greater than in the energy intensive one).

5.7.2 Platform supply vessel

Differently from what happened for the ferry, after several tests was found that a *"power intensive"* application of the storage is the best choice for the platform supply vessel (i.e. nominal current equal to 2 *C*). This, is mainly due to the irregular working behaviour of the PSVs (e.g. as proposed in Figure 67) and due to the stringent requirement of reserve of power that these ships have in DP3 conditions (e.g. the reserve of power for this case study was set equal to the 50% of the power demanded by the loads).

5.8 Results

The algorithm proposed in this work for the optimal selection, management of the power generation system is here applied to both the case studies, and the main results are proposed and analysed. As already stated, the main results of this optimization algorithm are size for the ESS, its optimum management, optimum scheduling (i.e. unit commitment) and dispatch for the DGs. Moreover, with reference to the unit costs of installation (i.e. for the ESS and the inverter), the specific fuel oil consumption curve and the unit cost of the fuel, it is also possible to evaluate the corresponding cost values (i.e. Mission cost and installation costs) both in short (e.g. mission horizon) and in long term (e.g. ship's life horizon).

5.8.1 Ferry

The main inputs to the algorithm have been already introduced in Table 62. It is to be noted that, being this a non-convex problem, there are several local minimum that can be chosen as possible solution by the solver. In this context, in order to prevent from finding a local minimum, tests have been performed and a region close to 400 kWh was selected as the nearest one to the global minimum. In this perspective, the starting point of the research has been set equal to 400 kWh, for this case study.

In fact, the main results proposed in Table 63 show that the best size of the ESS is close to the starting point of the research, i.e. equal to 395 kWh.

TABLE 63 – FERRY'S MAIN RESULTS

Parameters	Value
Energy storage system main characteristics:	
Size [kWh]	395
Nominal current	1C
P_{INV} [kW]	395
Energy storage system management:	

DoD_{avg} [%]	32
$N_{C_{Daily}}$	6.4
$N_{replacement}$	1.7
Mission cost (MC) analysis:	
MC (historical data) [$]	2610
MC (optimized) [$]	2418.5
Mission savings [$]	191.5
Mission savings [%]	7.3
Total cost (TC) analysis	
ESS installation costs [k$]	264.8
TC (historical data) [k$]	23817
TC (historical data) [k$]	22473
Total ship's life savings [k$]	1343
Total ship's life savings [%]	5.64

The results proposed in Figure 69 show the power generation system optimal management performed by the algorithm. These results are also summarized in Table 64 and it can be noted that the DGs are often loaded at their point of minimum fuel oil consumption (i.e. 90% of their rated power) and the number of starts and stops is limited to a maximum of 8 start-ups per day (e.g. for DG1 and DG3).

The mean, maximum and minimum loading conditions for DG1 are 76.9%, 110% and 30% of their rated power, respectively. For DG2, these values are all equal to 90%, instead for DG3, these are equal to 77.4%, 108.4% and 30%, respectively. Finally, for what concern DG4, the mean is equal to 88.4%, the maximum to 90% and the minimum to 30%. Consequently, significant saving in mission cost has been pointed out.

TABLE 64 - DG'S OPTIMUM MANAGEMENT, FERRY

Parameter	DG1	DG2	DG3	DG4
Avg load [%]	76.9	90	77.4	88.4
Min. load[%]	30	90	30	30

Max. load[%]	110	90	108.4	90
Start-ups	8	4	8	5

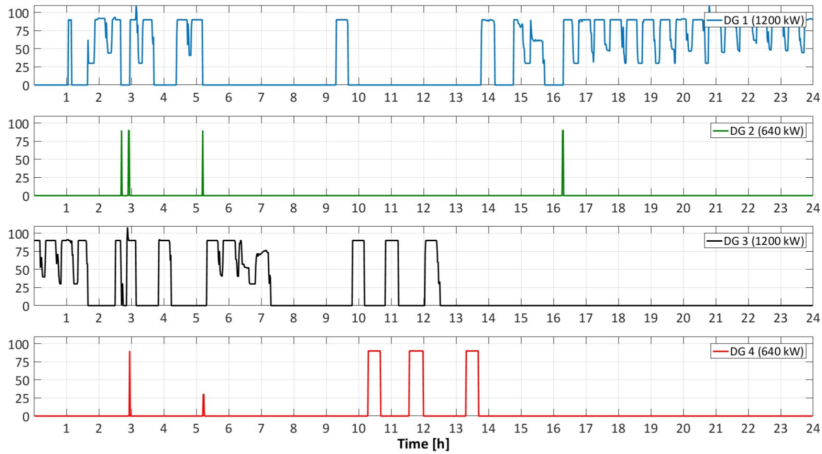


Figure 69 – DG's optimum dispatch and scheduling, Ferry

In Figure 70, the behaviour of the SoC and the power delivered by the battery are presented.

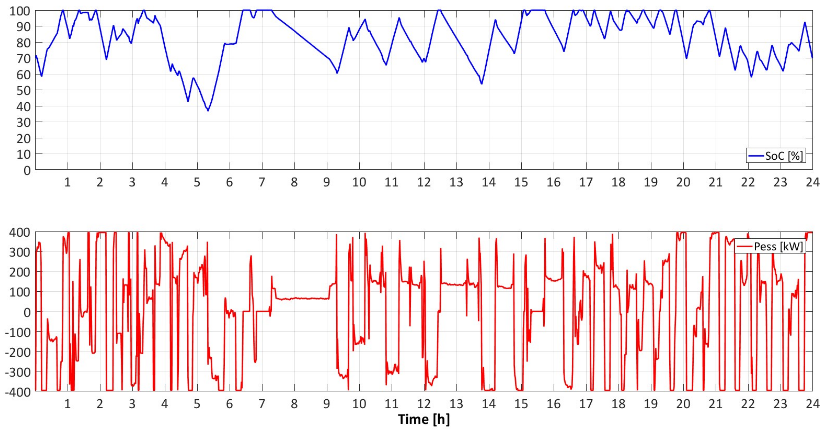


Figure 70 – ESS state of charge and power exchanged behaviour, Ferry

From the plot above, it is possible to note that the SoC is never below the minimum value SoC_{min} selected and, instead, it is often higher than the 60%. On the other hand, from the plot below, it is possible to see the behaviour of the power delivered P_{ESS_j} by the storage system along the whole mission time horizon.

In Figure 71, load power and power generated by the power system are proposed. The load is always covered by generation. Furthermore, there are time steps where the load is covered only by the storage system. The power generated by diesel generators presents a very constant behaviour. In fact, fluctuations in load are covered by the ESS, as expected.

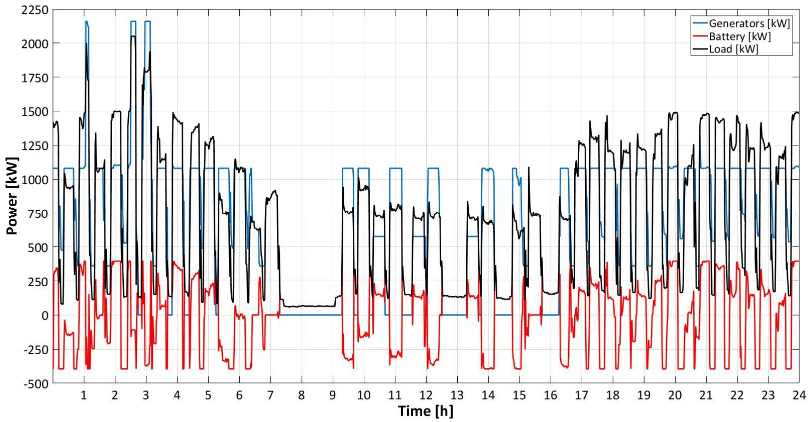


Figure 71 - Load power and power generated, Ferry

5.8.2 Platform Supply Vessel

As it happened for the ferry, also for the PSV the main inputs to the algorithm are those proposed in Table 62. For this case study, the starting point of research has been set equal to 755 kWh and the weights of the objective function have been changed in order to better fit the features of this case study. The main results obtained are those proposed in Table 65. In this case, results are reported considering 6 days of time horizon, instead of the single day considered for the ferry. The optimal size of the storage is equal to 755 kWh.

TABLE 65 – PSV'S MAIN RESULTS

Parameters	Value
Energy storage system main characteristics:	
Size [kWh]	755
Nominal current	2C
P_{INV} [kW]	1510
Energy storage system management:	
DoD_{avg} [%]	46.5
$N_{C_{Daily}}$	7.8
$N_{replacement}$	5
Mission cost (MC) analysis:	
MC (historical data) [$]	19605
MC (optimized) [$]	11632
Mission savings [$]	7973
Mission savings [%]	40.7
Total cost (TC) analysis	
ESS installation costs [k$]	3150.9
TC (historical data) [k$]	30041.3
TC (historical data) [k$]	20441.3
Total ship's life savings [k$]	9600
Total ship's life savings [%]	31.95

In Table 66 the main results for the diesel generators management are proposed. It can be noted that DGs are often loaded at their point of minimum fuel oil consumption (i.e. 90% of their rated power) and the number of starts and stops is limited to a maximum of 60 start-ups for DG1 (e.g. in six days of operation). The mean, maximum and minimum loading conditions for DG1 are 87%, 110% and 30% of their rated power, respectively. For DG2 and DG3, these values are all equal to 90%. Finally, for what concern DG4, the mean is equal to 87.8%, the maximum to 110% and the minimum to 30%.

TABLE 66 - DG'S OPTIMUM MANAGEMENT, FERRY

Parameter	DG1	DG2	DG3	DG4
Avg load [%]	87	90	90	87.8
Min. load[%]	30	90	90	30
Max. load[%]	110	90	90	110
Start-ups	60	1	1	50

In Figure 72, the loading conditions for the DGs obtained with the optimization algorithm are proposed. In comparison to those reported in Figure 68 for the historical data, it is possible to note that after this optimization they work closer to their optimum working point. It is to be noted that, for what concern DG 2, the spike at the 108 hour of the simulation corresponds to fifteen minutes of working, together with the DG 4. This is mainly due to the need of cover the total load and, at the same time, guarantee the optimal loading condition on the DGs. On the other hand, for what concern DG 3, the initial spike is due to the user's initialization of the DGs states.

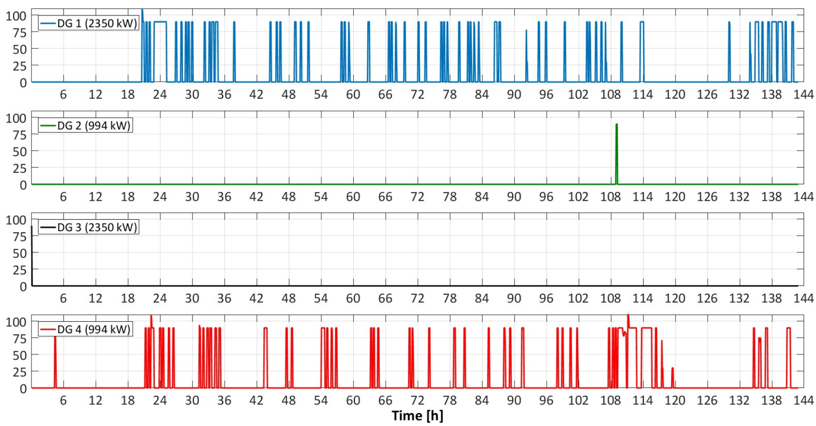


Figure 72 – DG's optimum dispatch and scheduling, PSV

In Figure 73, dynamic profiles of the battery state of charge SoC and power delivered P_{ESS_j} are shown. In Figure 74, load power and power generated by the power system for the PSV are proposed.

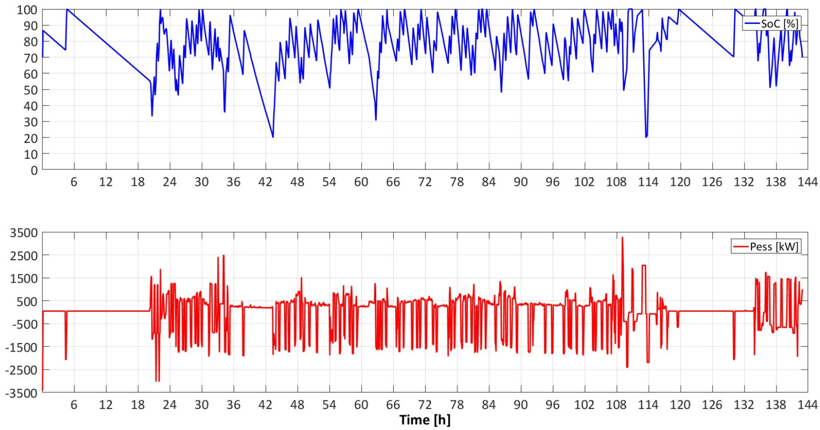


Figure 73 – ESS state of charge and power exchanged behaviour, PSV

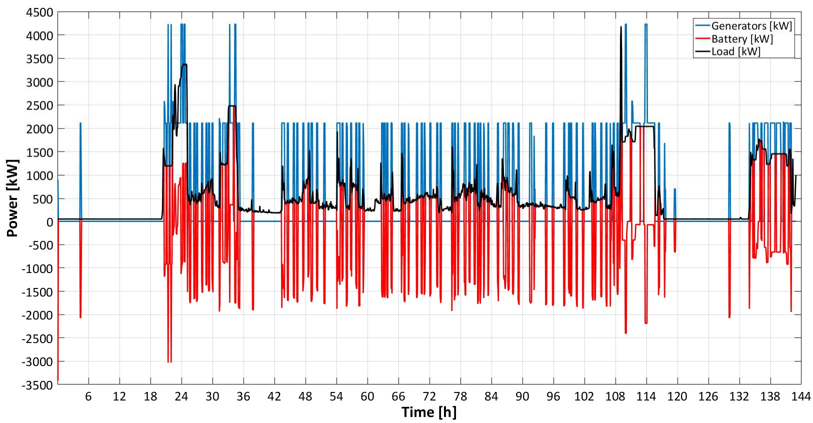


Figure 74 - Load power and power generated, PSV

The load is covered by generation in each time step of the simulation. Moreover, there are several time steps where the load is covered only by the storage system, often when the ship is *"at Anchor"* condition.

The power generated by diesel generators presents a very constant behaviour. In fact, also for the PSV, fluctuations in load due to variation in speed of adverse weather conditions are covered by the ESS, as well.

5.9 Conclusions

In this work, algorithms have been presented in order to optimally select and manage an ESS, when power demand profiles are available. These algorithms, applied to the case studies, have highlighted the possibility to improve the performances and, consequently, increase the savings of traditional power generation systems by introducing an ESS. In this context, the highest savings have been observed for the PSV, where the mission saving is close to 41%, and on the other hand, the net saving is close to 32% (i.e. those obtained considering the entire ship's life as time horizon), compared to those calculated with the recorded data.

However, good saving are also observed for the ferry, i.e. close to 6%, considering the net savings on the entire ship's life, even if these are modest compared to those presented for the PSV. These algorithms have been developed in a flexible and general way and can be applied to several shipboard power system configurations. Furthermore, also the ESS characteristics can be changed to consider different technologies as possible solution (e.g. batteries, flywheels and super-capacitors).

On the other hand, other important characteristics such as the volume, weigh and global efficiency of the power system would be considered in order to optimally design an energy storage system. Unfortunately, these information would not have been available for the ships considered as case studies. Future studies will consider the implementation into the EMS algorithm of the dynamic efficiency for the ESS and the whole power system, together with the introduction of renewable and alternative energy sources (e.g. PV system, micro-turbines and fuel cells).

6 DISCUSSION AND CONCLUSIONS

In the previous chapters, a detailed state of the art and literature review on the main methods to perform a load prediction, sizing the on board power generation system and energy storage systems have been reported. Considering the load prediction for shipboard applications, methods and approaches have been developed, formulated and explained to perform a probabilistic electrical power load analysis. This, in the perspective to overcome limitations of the traditional deterministic approach adopted in the last century. This method has been validated on two different case studies, a traditional bulk carrier ship and a modern large cruise vessel. The results yielded, if compared to those obtained applying the deterministic approach to EPLA, have shown a significant difference, especially for modern ships with an integrated power system (i.e. where both service and propulsion loads are powered by the on board power system). This difference is largely due to the factors applied in the traditional approach, which were evaluated with statistical analysis based on dated ship power systems (e.g. where the amount of electric power installed were significant lower than in modern ships). However, it should be noted that, the probabilistic method formulated in this thesis would require a validation based on experimental readings. This in the perspective to test the methodology and fix the statistical models for the electric devices, depending on their function and on the exogenous variables (e.g. air and water temperatures, humidity and ship speed).

Considering the optimum problem formulated in Chapter 4, significant reduction in the total power installed, installation cost for diesel generators and expected fuel oil consumption have been highlighted. A future improvement could consist in implementing additional generation technologies, where the cost function should also take into account the different contribution of the polluting emissions by varying the generation technology selected.

Further, concerning the optimum method to select the technology and size of an on board storage system, reduction in management costs close to 30% have been found. Depending on the ship under examination, this method may justify or not the installation of an energy storage system on board the ship. A future development of this method would be a connection with the probabilistic approach to EPLA. This, considering the possibility to performs the load forecasting (i.e. the load behaviour depending on time) adopting the results obtained with the probabilistic EPLA. In fact, this methodology could allow obtaining the total load behaviour in time, without using simulation models of the system. Nevertheless, it is clear that this method, combined with those presented in this thesis, could allow an optimal design, selection and sizing of the whole generation system.

Finally, it would also be desirable to develop *demand side management* (DSM) techniques, similar to those applied in terrestrial applications, which could account, also in design phase, of the amount of power that can be managed on board the ship. In fact, beyond the *load-shedding* techniques already present on modern ships, DSM is still today an unexplored topic for naval applications, despite it could guarantee beneficial effects both in design and in management perspectives.

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