Dalia Casanova Mombiela

Power Plant Design Optimization at the Ship Preliminary Design Phase

'Digital Twin to Design'

Masteroppgave i Marin teknikk
Veileder: Mehdi Zadeh
Juni 2021

Masteroppgave

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Kunnskap for en bedre verden

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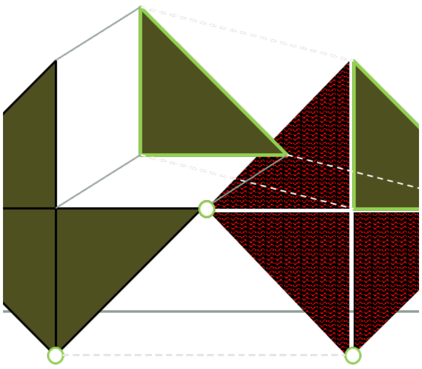

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Contents

List of Figures iii

List of Tables v

1 Introduction and Research Gap 2

2 State of the Art, sustainable power systems and data driven models 4

2.1 Sustainability, "the bussines of bussines" . . . 4

2.2 Power plant design, history and state of the art . . . 10

2.3 Curve fitting techniques . . . 16

3 Methodology 20

3.1 Data Processing . . . 23

3.1.1 Load profile . . . 23

3.1.2 Relational Data Table . . . 26

3.1.3 Energy measurements . . . 31

3.1.4 Batteries capacity reduction per cycle . . . 34

3.2 Algorithm structure . . . 38

3.2.1 Assumptions . . . 38

4 Case Study 43

4.0.1 Full Electric Mode, FEM . . . 46

4.0.2 Fossil Fuels Hybrid Mode, FFHM . . . 50

4.0.3 Fossil Fuels Mode, FFM . . . 52

5 Results Discussion 54

5.1 FEM . . . 54

5.2 FFHM . . . 56

6 Conclusions and Future Work 58

Bibliography 60

Appendix 62

A EEDI Calculation **63**

B Machinery Raw Data **66**

A Gensets 66

B Batteries 66

C Algorithm Matlab Code **68**

A FEM 68

A.1 1_{st} LOOP 68

A.2 2_{nd} LOOP 73

D Publications **78**

List of Figures

1 CO_2 emissions VS annual GDP for analysis . . . 5
2 CO_2 emissions estimation . . . 8
3 Emission Control Areas . . . 9
4 Design spiral, J.H. Evans 1959 . . . 10
5 Existing ship propulsion systems . . . 13
6 Engines Data Analysis . . . 14
7 Specific Energy and Power densities . . . 16
8 Curve fitting methods, Matlab . . . 17
9 Power Generation Existing Combos . . . 21
10 Full Project Structure . . . 23
11 Load Profile . . . 24
12 Load Profile Indexes . . . 25
13 RDT concept . . . 26
14 Multi-structure curve fitting basic principle . . . 27
15 Multi-structure curve fitting concept . . . 27
16 Curve fitting functions . . . 28
17 Mean error shape . . . 30
18 Energy Measurement Error . . . 32
19 Operational Feasibility Check . . . 33
20 Capacity Reduction per Cycle . . . 36
21 Total Costs Function . . . 41
22 Kasteelborg drawing . . . 43
23 Energy Released - Current Installation . . . 45
24 Machinery Input Data . . . 46
25 Full Electric Mode, OSV . . . 47
26 Energy demand case study . . . 48
27 Energy measurement error . . . 49
28 FEM Costs Optimization Concept . . . 50
29 FFHM Costs Optimization Concept . . . 51
30 Energy-Power profile system sizing dependencies . . . 52

31 FFM Calculation 53
32 Load Profile Reduced 54
33 OPEX among time 55
34 Sum. of spec. costs among the load profile - L1 56
35 Sum. of spec. costs among the load profile - L2 56
36 Spec. costs among time - L1 56
37 Spec. costs among time - L2 56
38 Total costs among time - L1 56
39 Total costs among time - L2 56

List of Tables

1 NOx emissions limits from MARPOL 9

2 Ship class notation from DNV 11

3 Exsisting alternatives in the market for the power plant configuration 12

4 Caterpillar marine engines classification for expected performance 14

5 Existing CAT Gensets - General Specifications 14

6 Load Profile Indexes for analysis 25

7 Test results to identify the common pattern of each function type 31

8 Minimums location in percentile units from the center of the sample to both sides 31

9 Capacity Reduction per Cycle Mean 36

10 EACCI & EMXI resulting values for 262800 cycles for % of them at three different DODs 37

11 Expected Number Of Batteries sizing error from the computing error of the capacity reduction per cycle insertion 37

12 Constraints Matrix Between Components 39

13 Feasibility matrices insertion from the overall perspective and the present scope . . 40

14 Feasibility Environment first simplification 42

15 KASTEELBORG current class notation from DNV. 43

16 KASTEELBORG Project Specifications 44

17 Gensets loading of the currently installed Generating Sets 44

18 Project Specifications FEM 46

19 left-right: NOBs feasibility; NOBs conforming the battery pack each autonomy, DOD_{MAX} and battery type selection 54

20 Gesnsets selection for algorithm testing 66

21 Fuel consumption from Gensets selection in g/kWh. 66

22 Batteries selection for algorithm testing 67

Nomenclature

BHP Break Horse Power

BMS Battery Management System

DHP Delivered Horse Power

DNV Det Norske Veritas

DOD Depth of Discharge

ECA Emissions Control Area

ECU Engine Control Unit

$EEDI$ Energy Efficiency Design Index

$EEXI$ Energy Efficiency Existing Ship Index

EHP Effective Horse Power

EMS Energy Management System

EPA United States Environmental Protection Agency

$FCVR$ Fast Commercial Vessel Rating

GDP Gross Domestic Product

GHG Global Greenhouse Gas

GT Gross Tonnage

IMO International Maritime Organization

LFP Lithium Iron Phosphate, $LiFePO_4$

LHV Low Heating Value

LLO Low Loading Operation

LTO Lithium Titanate Oxide

$MARPOL$ International Convention for the Prevention of Pollution from Ships

MCR Maximum Continuous Rating

$MEPC$ Marine Environment Protection Committee

NCR Normal Continuous Rating

NMC Nikel Manganese Cobalt Oxide, $LiNi_{1-x-y}Mn_xCo_yO_2$

PTI Power Take In

PTO Power Take Off

Q_N Nominal capacity

$SEEMP$ Ship Energy Efficiency Management Plan

$SOLAS$ International Convention for the Safety of Life at Sea

SOS State of Charge

TBO Time Between Overhauls

Abstract

An algorithm for ship power plant optimization at the step of the preliminary design of a ship is presented here. The document establishes the bones and identifies the intervening factors for a ship power plant first sizing algorithm to where include further data and detailed analysis. It is presented as a first step of a complete project which structure and accuracy is expected to improve each new case study for analysis ending up with a standard pattern for the design of the power plant considering the project nature, ship design specifications, existing installation components, detailed models feedback, the operational profile of the ship and client wishes. The outcome of the algorithm is a scope of optimum solutions within specific operational behavior bandwidths of the system together with different indexes evaluating how the optimum scenario changes out of those.

The retrofit project evaluation of an Offshore Service Vessel is selected in three different design modes.

This first step integrates part of the knowledge acquired during the M.Sc. in Marine Technology studies from different fields, establishing the links from where they can work together. Going from data processing techniques used for optimization purposes to marine machinery environments understanding and real analysis ending up with clean energy enhancements achieved thanks to new control systems strategies research. Nevertheless, the project ended up from the author perspective as an interesting research gap solution from where to continue new approaches, useful in a short term for new power plant topologies' flaws identification and in a long term as a generic tool to help with the power plant design, considering an updated market perspective and specific ship project environments.

Abstrakt

Her presenteres en algoritme for å optimalisere skipskraftverk i startfasen av skipsdesignprosessen. Oppgaven etablerer strukturen for hvordan en skal avgjøre størrelsen på kraftverket om bord og identifiserer hvilke faktorer som gjør at ytterligere data og analyser er nødvendige. Algoritmen er første steg i et større prosjekt, der både strukturen og nøyaktigheten på algoritmen forventes å bli bedre for hvert steg. Gjennom å se på flere systemer vil både designprosessen som tar i bruk algoritmen og algoritmen forbedre seg, slik at integrasjon av algoritmen gir merverdi for alle parter. Det langsiktige målet for algoritmen er å komme fram til en standardisert metode for å designe kraftverk for skip. Algoritmen produserer flere alternativ til oppsett av kraftsystemet til skipet, der alle er optimale løsninger for en gitt operasjonsprofil, i tillegg til hvordan optimalsystemet kommer til å endre seg basert på hvordan andre faktorer i prosjektet endrer seg.

Prosjekteringsevaluering av et OSV i tre forskjellige designmodus.

Dette første steget er basert på kunnskap opparbeidet gjennom en mastergrad i Marin Teknikk. Kunnskapen brukt kommer fra flere ulike akademiske felt, og etablerer hvordan disse samarbeider for å finne løsningen. Dataprosesseringsteknikker er brukt som er verktøy innen optimering, forståelsen for marint maskineri har vært essensielt for å forstå hvordan systemer er satt opp til dags dato, og kontrollteori har blitt brukt til å finne metoder for reduksjon av energitap. Fra forfatterens perspektiv har prosjektet vært et bra steg for å finne ut hvor akademisk kunnskap har vært mangelfullt, og har etablert hvor mer forsking er nødvendig. Prosjektet har vært nyttig for å finne hvor topologien til dagens systemer feil, selv om målet på lang sikt er å lage et generisk verktøy for design av kraftsystemer om bord på skip. Det endelige produktet vil være i stand til å ta inn faktorer fra markedet og hvilke miljøer et skip kommer til å befinne seg i for å finne den optimale løsningen.

1 Introduction and Research Gap

Consequent to the increasing developments in marine electrification [5], [33], and alternative marine fuels [13], the design of the on board power systems has been a crucial issue to meet the ship mission and operational requirements,e.g., total power demand, while evaluating KPIs and design optimization variables, such as reduced costs or emissions. However, the existing systems design guidelines for ships are not yet mature and they are usually based on minimum safety ranges, translated into challenging implementation for systems optimization goals. However, the on board systems control settings and load profile have significant effect on an optimum design of the power system. Hence, a first step to optimize the design results is to consider the system performance under operation, using real systems data storage properly scaled up or processing data from specific system configurations under research such as the one in [22].

The closest structure to the proposed "Digital Twin to Design" approach include different EMS developments with deeper system behaviour studies integrating machine learning techniques, e.g., [24] for vessels having cyclic operations, or the ongoing research around fuel consumption reduction by in-stalling storage elements which requires of power management strategies to evaluate its optimization [9]. Nevertheless, this work re-structures the procedure of calculus where a robust core is aimed to be used and further improved each case study of analysis. The main outcome of the algorithm changes from areal time conditioned operation signals tight to a specific case study to a problem formulation focused on the preliminary design phase accuracy which first cares about the power plant external design links to scope a feasible scenario of solutions with its correspondent optimum operational bandwidths

The present assessment gathers a first step on a complete algorithm elaboration for power and propulsion systems design optimization on board at the step of preliminary design of the ship targeting the main components sizing and considering the whole project nature. A first conference paper has been published in IEEE Transportation Electrification Conference and Expo 2021 gathering fist steps and structure of the present project development, Appendix D.

The structure of document includes five chapters:

1. **Literature Review:** In this section a transition from the sustainability concept in the maritime sector to the power plant design impact is done, followed by more technical details on the sustainability concept implementation from rules and regulations within different maritime environments. A separate section regarding curve fitting techniques is included in favour to the algorithm data processing requirements.

2. **Methodology:** The method is separated into two main environments. Data processing of the algorithm is the first one, including curve fitting proposed environment of analysis, energy computing error estimations and capacity reduction per cycle from storage elements calculus for the required accuracy at the preliminary design step of the ship. The second one presents the algorithm structure and development.

3. **Case Study:** Then, an Offshore Supply Vessel is presented for a retrofit power plant design analysis under the proposed algorithm structure.

4. **Results Discussion:** Results from full electric mode deep analysis, conceptual evaluation of the hybrid solution and results from the fossil fuels mode applied to the existing installation are presented in this section.

5. **Conclusions:** A summary with the main project highlights is finally done from the subjective evaluation to the technical objective results with the consequent error track and proper interpretation considering the missing data for evaluation at the present scope.

2 State of the Art, sustainable power systems and data driven models

2.1 Sustainability, "the bussines of bussines"

After the commitment of 196 Parties to the United Nations Framework Convention on Climate Change at COP21, in Paris on December the 12^{th}, in 2015, the maritime industry keeps researching for further alternatives which allows the sector to reduce CO_2 and GHG emissions. The Paris Agreement turn the sustainability concept into an international business strategy useful to keep new industrial developments closed to environmental-committed solutions.

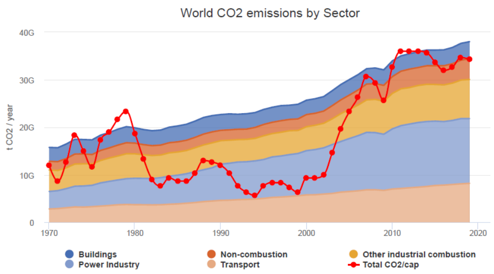
The Paris Agreement is the first-ever, legally binding global climate change agreement. Governments agreed on different emissions mitigation policies to be implemented:

- Long-term goal on keeping the increase in global average temperature to well below 2°C.
- To limit the increase to 1.5°C.
- To peak global emissions as soon as possible considering developing countries.
- To undertake rapid reductions thereafter in accordance with the best available science, so as to achieve a balance between emissions and removals in the second half of the century.

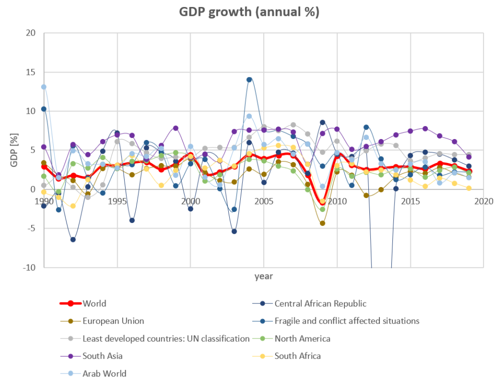
While Paris Agreement identifies climate change as a fight for all countries enrollment under emissions reduction commitment, Kyoto Protocol calls just developed countries to aim for it. This protocol entered into force by 2005 and was adopted by 192 parties. As described in [8], "*Kyoto Protocol operationalizes the United Nations Framework Convention on Climate Change by committing industrialized countries and economies in transition to limit and reduce greenhouse gases (GHG) emissions in accordance with agreed individual targets. The Convention itself only asks those countries to adopt policies and measures on mitigation and to report periodically*".

Averaged as a whole, the global land and ocean surface temperature for March 2020 was 1.16°C, [27]. As illustrated in [1] GHG emissions include carbon dioxide (CO_2) by burning fossil fuels (coal, gas natural and oil), solid waste, trees and other biological materials and as a result of some chemical reactions, e.g. manufacture of cement; methane (CH_4) produced with the transport of coal, natural gas and oil, some practices from agriculture, land use or from the decay of organic waste in municipal solid waste landfills; Nitrous oxide (N_2O) from agricultural and industrial activities, combustion of fossil fuels and solid waste and treatment of wastewater; and fluorinated gases from a variety of industrial processes. Considering the definition from EPA of GHG, "*gases that trap heat in the atmosphere*", water vapor and ozone are part of them but essential for life so not considered here as a targeted gas for emissions reduction.

Figure 1a shows the CO_2 emissions scenario per year from 1970 to 2020 from where it is appreciated a slight emissions reduction from 2015 after a huge increase around 2005. Figure **??** shows the Gross Domestic Product for the world but also for specific zones. These pictures are exposed together for a conceptual evaluation or a high label reflection around them with no deeper economical analysis, which keeps out of scope, but as a door opening for further analysis on sustainability concept inclusion in the market and the consequent economy transition.



(a) World CO_2 emissions by sector [11]



(b) GDP annual growth (annual %) [4]

Figure 1: CO_2 emissions VS annual GDP for analysis

"*GDP measures the monetary value of final goods and services. That is, those that are bought by the final user produced in a country in a given period of time*", [16]. While CO_2 emissions experienced a peak and a later stabilization around 2015 the world's GDP also remains stable and it is noticeable the GDP increment in the European Union. Conflict affected countries reduced its GDP fluctuations around 2015 and South Asia increased its GDP. In general terms the graph shows how underdeveloped and developing countries with low income rates are much less affected by world economical crisis, e.g. the Global Financial Crisis in 2007-2018. The impact of the energy transition relays not only on GDP changes but in many different economical aspects, nevertheless it could contribute to extract an economy movement tendency which just has started, following sustainability goals which affects to the maritime sector in the shape of GHG emissions reduction or even emissions removal goals. The impact of the measures to get the expected goals should ensure for no negative impact on the maritime economy, specially in the maritime transport field declared, in the United Nations Conferece on Trade and Development report of 2018, the backbone of international trade and the global economy, covering around 80 per cent of global trade by volume and over 70 per cent of global trade by value worldwide.

Global regulatory agencies as U.S. Environmental Protection Agency (EPA), European Commission or IMO itself enhanced programs and strategies to reduce GHG emissions. Extracted from [10] European Union strategy steps are monitoring, reporting and verification of CO_2 emissions from large ships using EU ports, greenhouse gas reduction targets settings and some more market-based measures in medium and long term. IMO established an IMO Data Collection System which requires owners of large ships (above 5000 GT) to engage in international shipping to report information on fuel consumption to the flag States of those ships. IMO GHG emissions reduction targets, which are the upper bound to the regional targets established each country, are the following ones:

- To reduce total annual GHG emissions from shipping by at least 50% by 2050 compared to 2008 levels.
- To pursue efforts to phase them out as soon as possible in this century.

In May 2005 IMO included Annex VI inside MARPOL and, with it, preventive limitations of air pollution from ships. It set limits on sulphur oxide and nitrogen emissions from ships exhausts and prohibits deliberate emissions of ozone depleting substances. Additionally, Annex VI defines emission control areas and since 2011 it adopted mandatory technical and operational energy efficiency measures for reducing greenhouse gas emissions from ships.

Under its pollution prevention treaty (MARPOL), and following the already mentioned goals from the Paris Agreement, IMO defines different levels of ambition to pursue its targets, [29]:

1. Carbon intensity of the ship to decline through implementation of further phases of the Energy Efficiency Design Index (EEDI) for new ships. Dynamical restrictions open to be tightened and well suited for different ship types.
2. Carbon intensity of international shipping to decline. To reduce CO_2 emissions per transport work, as an average across international shipping, by at least 40% by 2030, pursuing efforts towards 70% by 2050, compared to 2008.
3. GHG emissions from international shipping to peak and decline. To reduce the total annual GHG emissions by at least 50% by 2050 compared to 2008 whilst pursuing efforts towards phasing them out as called for in the vision as a point on a pathway of CO_2 emissions reduction consistent with the Paris Agreement temperature goals.

On one side, the executive summary of DNV's Energy Transition Outlook 2020 expects alternative carbon-neutral fuels to be an essential element for achieving IMO's GHG emissions reduction goals for 2050 and they consider them the only practical way for shipping to achieve the ultimate vision of full decarbonization as soon as possible before 2100, [12]. From this outlook, the maritime forecast up to 2050 includes a list of global policy measures for emissions reduction, in short and long term, highlighting the EEDI, with increasing tightening measures, for new construction vessels and the Energy Efficiency Existing Ship Index (EEXI), included as further amendments to MARPOL Annex VI in 2020 and subject to adoption at MEPC 76 in June 2021 for entering into force in 2023. EEXI will be applied to vessels over 400 GT inside the affected parties of Annex VI, from MARPOL, being the ones with diesel energy sources installated with a total power larger than 130 kW, built and installed since 1^{st} January 2000. Annex VI of MARPOL limits discharges into the atmosphere of volatile organic compounds, SO_x from fuel oils and NO_x from diesels combustion. Maritime forecast from [12] also includes as policy measures the Ship Energy Efficiency Management Plan (SEEMP) enhancement and carbon intensity indicators from a short term perspective in all ships, and alternative fuel drop-in requirements, CO_2 price and fuel carbon limitations in a long term perspective.

EEDI requires a minimum energy efficiency level per capacity mile for different ship type and size segments, [29], grams of CO2 per tonne mile, and it evaluates the ship efficiency by means of **propulsion power** and transport work. The level is to be tightened incrementally every five years simulating continued innovation and technical development of all the components influencing the fuel efficiency of a ship from its design phase. The level was set to 10 10% since January the 1^{st} after two year phase zero. It is important to mention that the index has been developed for the merchant fleet and embraces emissions from new ships inside tankers, bulk carriers, gas carriers, general cargo ships, container ships, refrigerated cargo carriers and combination carriers; extended from 2014 to LNG carriers, Ro-Ro cargo ships, Ro-Ro cargo & passenger ships and cruise passenger ships having non-conventional propulsion (out of diesel-electric, turbine and hybrid), all them responsible for the 85% of the CO_2 emissions from the international shipping, [29]. Additonally, the MEPC adopted guidelines for assisting the index implementation, most of them consulted for the present project and available at [29]. Germanischer Lloyd published in 2013 guidelines for determination of the Energy Efficiency Design Index, [21] from where to highlight here for the present project use:

- EEDI is calculated as maximum allowable value, using the 100% of the dead weight at summer load draft, except for passenger ships where GT is used.

- Capacity units are dependent on ship type and also defined in the rules' guidelines.
- The EEDI calculation and verification process includes two steps, preliminary and final EEDI calculus.
- **Input data for the calculation:** C_F, Δ, DWT, $f_{eff(i)}$, f_i, f_j, f_w, GT, Lightweight, P_{AE}, $P_{AEeff(i)}$, $P_{eff(i)}$, $P_{ME(i)}$, $P_{PTI(i)}$, $P_{PTO(i)}$, $SFC_{AE(i)}$, $SFC_{ME(i)}$, V_{ref}. (not mature for dual fuel engines). Its definition and calculations are included in [21] and redefined from the preliminary EEDI to the final one.
- Annex C reefers to the calculation of the auxiliaries load's power, P_{AE}, via intermediate step first calculating P_{load} as the contribution from each energy producer.

The calculation of P_{load} is considered here as a potential standard breakdown for analysis of potential improvements of energy savings.

From EEDI determination guidelines, [21], the formulas from Appendix A are inserted in the present project, although they are just a first step to be analysed with further feedback from higher accuracy models or new research. **From the presented formulation it is extracted the extreme dependency of a proper EEDI calculation on a good estimation of the machinery power output already considered at the design step**. These currently used calculations consider a power output maximization which is not well suited to optimized the power plant design. **EEDI is going to be one of the optimization indexes from the emissions optimization box to consider in the presented algorithm for new construction ship design projects**.

Figure 2 illustrates all dependencies to estimate gramms of CO_2 following EEDI's calculation guidelines, described in detail inside Appendix A. The present algorithm follows this approach to optimize the amount of CO_2 for different power plant combinations to find the link with the present regulation and make it reliable for all users. Then, number of elements, e.i. main engines, auxiliary engines, additional technologies for efficiency improvement, innovative technologies for energy production, PTO and PTI systems, together with the rated values to individually characterize each, e.g. rated power, are the variables to be calculated for emissions and cost minimization and safety maximization. These variables are currently just estimated with a maximization approach, e.g. the main engines output power is calculated as the 75% of the total installed power. If following this path for analysis there is no way to get a proper design optimization which requires some estimated operation data to approach the final design into optimum emissions ranges and, even the index itself is challenging to be re-evaluated.

An additional box to estimate EEDI value each power plant design solution is expected to be included in future work. Nevertheless, and considering the first case study as a retrofit one, EEXI calculation box will be first inserted and tested pointing mainly on CO_2 amounts calculation part to be minimized and the required structure and input data to finish the index calculations.

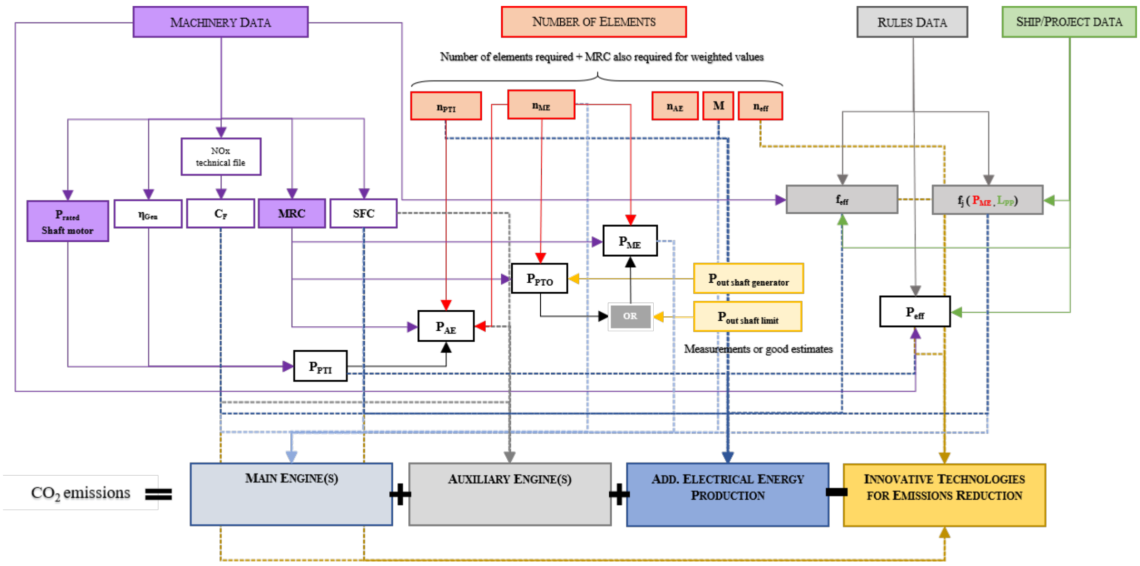


Figure 2: CO_2 emissions estimation inside EEDI calculation, variables and dependencies

EEXI calculation follows the guidelines from 2018 for EEDI's calculation, [30], and specific ones will be adopted after MEPC 76 in June 2021. As for EEDI, EEXI is a design index, not an operational index, which determines the standarized CO_2 emissions related to installed engines power, transport capacity and ship speed (function of installed power). The index just refers to the design of the ship but this project claims for the need of a proper operation profile estimation to get an optimum design for the ship specific purpose. EEXI is applied to almost all oceangoing cargo and passenger ships above 400 gross tonnage including different correction factors dependent on the ship type for a better estimation. The main different between EEDI and EEXI is that there is no need for sea trials within EEXI certification and the ship speed is determined from model tests speed/power curves output or from the given formula based on ship type and installed power, with no doubt which is a conservative way.

Currently, international shipping claims for maritime emissions taxation to force its reduction. The European Parliament already voted in September 2020 in favour of including GHG emissions from the maritime sector in the European Union's carbon market from 2022, [26]. Since 2018 the option to include CO_2 has being seriously considered with different studies such as the one from the International Monetary Fund in 2018, [18]. Emissions taxes have not being so far adopted in the international maritime sector, considering that they are rated around 2.5% of the GHG emissions.

From January 2007 Norway introduced taxes on NOx emissions from ship engines above 750 kW with a rate of 1,765/ton and applied to all ships within Norwegian territorial waters irrespective of the nationality, [17]. As stated in [17], for Norwegian registered vessels, the tax applies to emissions in "near waters" and ships in international traffic are exempt, including vessels operating in direct traffic between Norway and foreign ports. The tax is calculated on the basis of actual NOx emissions. If these are not known, it is calculated based on IMO NOx emissions limits. Since the introduction of the NOx tax, 15 Norwegian business organizations entered into an Environmental Agreement on NOx with the Ministry of the Environment to reduce the effective tax for the offshore sector – which led the formation of the NOx Fund. For SOx emissions there are no taxation but is one of the main targets for emissions reduction and monitoring of IMO, since shipping accounts in Europe approximately for the 20% of the total SOx emitted.

Emissions Control Areas (ECAs) were IMO designated for them to adopt special mandatory measures for emissions from ships required to prevent, reduce and control air pollution from NOx, SOx and particulate mater. Figure 3 delimits the existing ECAs:

1. the North American Emission Control Area, which means the area described by the coordinates provided in appendix VII to Annex VI of MARPOL;
2. the United States Caribbean Sea Emission Control Area, which means the area described by the coordinates provided in appendix VII to Annex VI of MARPOL;
3. the Baltic Sea Emission Control Area as defined in regulation 1.11.2 of Annex I of MARPOL; and
4. the North Sea Emission Control Area as defined in regulation 1.14.6 of Annex V of MARPOL.

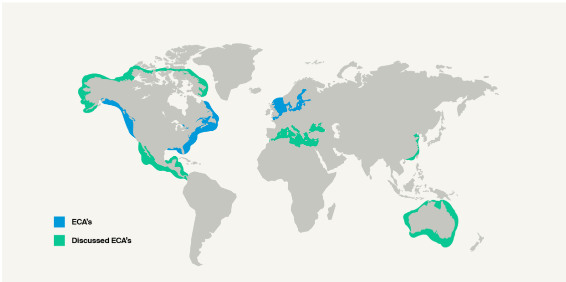


Figure 3: Emission Control Areas from MARPOL

Considering no emissions taxes worldwide, the projected algorithm does not include them into the cost optimization environment. Nevertheless, the optimization environment minimizes the total emissions results among the specified operational profile. The calculation of the overall NOx will be determined form the same components disclosure EEDI calculus follows, included in Appendix A, but changing CO_2 conversion factor, from fuel oil to CO_2 or CO_2 emissions curves from engines, to NOx engines curves. SOx emissions are inserted just in case the engine manufacturers provide also SOx curves within the engines specifications. Nevertheless, each algorithm run should specify the fuel type to be used on board each machine, just considering the ones which comply with regulations on sulfur content limit from MARPOL.

NOx emissions limits per diesel engine from MARPOL are included in table 1. The sulfur content limit in fuels used from MARPOL is set to 0.5%m/m for all vessels and to 0.10%m/m for ships operating within an ECAs.

Table 1: NOx emissions limits from MARPOL

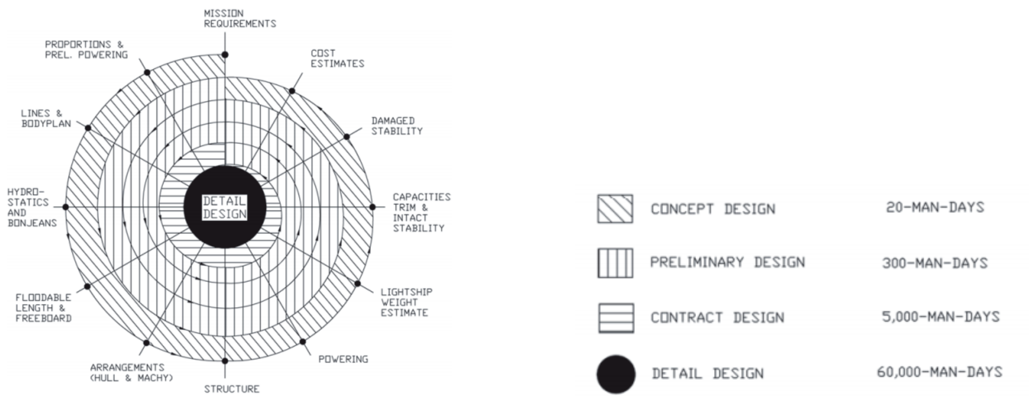
Marine Diesel Engines

Tier	**construction year on or after**	**Zone**	**NOx limit [g/kWh]** n <130 [rpm]	130 n <2000 [rpm]	n 2000 [rpm]
			n = rated engine speed		
I	2000	all	17,00	45 x n(-0,2)	9,8
II	2011	all	14,4	44 x n(-0,23)	7,7
III	2016	North American ECA or the United States Caribbean Sea ECA	3,4	9 x n(-0,2)	2
	2021	Baltic Sea ECA or the North Sea ECA			

2.2 Power plant design, history and state of the art

The present section briefly analyses the power plant design as an increasingly important part of the ship design, transitioning from the common procedures to tackle the ship design at its preliminary design phase to the power plant design history, then going through the commonly used methods to estimate the power and propulsion systems sizing, at the same stage, ending up with the power plant components inserted in the presented algorithm for a deeper analysis.

Since the 1950's ship design relays on the "ship design spiral", Figure 4, presented by J.H. Evans in 1959 and still mentioned in many currently used literature for ship design as the one in [32]. The same author, as an editor this time, approaches the Risk-Based Design, strongly linked with SOLAS (1974) requirements, focused on the improvement and compliance with safety levels of life at sea, following the Safety Level Approach (SLA) from Goal-Based Standards (GBS) introduced by the Maritime Safety Comittee (MSC 81/6/2). Safety Level Approach uses IMO approach to risk acceptance by defining reliability levels at different labels, ship, ship function, system, subsystem or components one. Then, different concepts came up as probabilistic damage stability, covered by regulation 25 of SOLAS, risks analysis, specially considered at the offshore industry, reliability analysis for power and propulsion systems and structures, fire safety analysis or the Formal Safety Assesment (FSA) developed by IMO as a tool to support decision making [6]. Goal-Based Standards target was also a good way to introduced the shipping industry knowledge into new design processes establishing the goals, e.g. safety levels, from different accident scenarios.



(a) (b)

Figure 4: Design spiral, J.H. Evans 1959

Most recently Computational Ship Design was targeted by Myung-II Roh and Kyu-Yeul Lee in [23] where the commonly manual calculation work when tacking ship design is simplified with systematic methodologies which can be introduced in a computation environment. Nevertheless, these methods still relays on well known approaches from ship models testing to real ship environments calculations and simple estimations based just on ship speed and total ship resistance when targeting the power requirements for the power plant design.

Inside book [23] the terms used to evaluate speed and power, coming together most of the time for ship design, are service speed at NCR power with a sea margin; Effective Horse Power (EHP) as the required power to maintain the intended speed of the ship; Delivered Horse Power (DHP) as power delivered to the propeller with some power loss; Brake Horse Power (BHP) as power at the crankshaft coming out of the main engine; Normal Continuous Rating (NCR) as power at which the main engine can be operated most efficiently, economically and with least maintenance

(85 ∽ 95% MRC); Maximum Continuous Rating (MCR) or Dearated MCR as the maximum power that can be produced by the main engine continuously without causing failure to propulsion machinery; and Nominal MCR (NMCR) as the maximum power of the main engine provided by the engine manufacturer. From this approach, the power plant sizing estimation starts after the hull roughness and still-air resistance calculation or so called model-ship correlation resistance for new construction vessels, followed by the total resistance estimation. Then the next step is the prediction of propulsion factors with, first, the different efficiencies performance, e.g. propulsive, propeller in open water, hull, relative rotative (...) efficiencies; afterwards, EHP as a function of ship speed and total resistance translated into Thrust Horse Power (THP) by including hull resistance, becoming to Delivered Horse Power implementing further resistances of propellers and rotative machines; and continuing with the efficiencies implementation approach up to the final BHP considering:

$$EHP < THP < DHP < SHP < BHP \tag{1}$$

$$NCR = BHP_{calm-water}\left(1 + \frac{SeaMargin}{100}\right)[W] \tag{2}$$

$$MCR = \frac{NCR}{EngineMargin}[W] \tag{3}$$

Finally, to calculate the main engine fit with the projected ship power plant the applications recommendation each brand, the propeller efficiency, weight and space taken by the engine in the machinery room with the correspondent arrangement, the initial investment cost and the operation cost are taken into account. All these calculations are tackled individually each new project, either retrofit or new construction.

Although these calculations comply with high standards of safety, all mentioned ship design perspectives name ship mission requirements or operational profile definition from the conceptual design as a first step together with the market analysis previous ship design estimations but, they are not significantly reflected when estimating the final power requirements for the power plant design. For the inclusion of a first mission the overall environment of design must be identify as a specific ship type environment extracted, for instance, from a class society definition as DNV, where a ship class notation is established and presented in Table 2. With a proper project environment understanding the power plant design could significantly be optimized from this stage not just in safety but also around total costs or emissions.

Table 2: Ship class notation from DNV

Dry cargo	***Container***	***RO-RO***	***Passenger***
General	Container	RO-RO	Passenger
Multi-purose	***Non-shelf-propelled vessels***	Car carrier	Ferry
Bulk carrier	Barge	***Compressed gas tankers***	***Oil tankers***
Ore carrier	Pontoon	Tanker for compressed natural gas	Tanker for oil
X carrier	***Liquefied gas tankers***	***Offshore service vessels***	Tanker for oil products
Great lakes bulk carrier	Tanker for liquefied gas	Offshore service vessel	Barge for oil
Chemical tankers	Tanker for C	Standby vessel	Barge for oil products
Tanker for C	Barge for liquefied gas	***Vessel for special operations***	Bulk carrier or tanker for oil
Tanker for chemicals	Barge for C	Crane vessel	Tanker for oil products with flashpoint above 60^{o}C
Barge for chemicals	FSU for liquefied gas	Cable laying vessel	Tanker for asphalt/bitumen
Barge for C	FSU for C	Pipe laying vessel	Barge for oil products with flashpoint above 60^{o}C
Tanker for chemicals with flashpoint above 60^{o}C	***Fishing vessels***	Semi–submersible heavy transport vessel	Barge for asphalt/bitumen
Barge for chemicals with flashpoint above 60^{o}C	Fishing vessel	DSV (SAT)	Bulk carrier or tanker for oil products
	Stern trawler	DSV (Surface)	
	Naval vessels	DSV (Ready)	
	Naval	DSV (OCS)	
	Naval landing craft	Seismic vessel	
		Welll simulation vessel	
		Fire fighter	
		Icebreaker	

According to [32] yearly ships costs from machinery and fuel, in CAPEX and OPEX terms, could cover from the 42% to the 61,5% of the overall yearly costs of the ship. Decisions taken at early stages of the design could have a great impact on the whole ship life. Nowadays, this stages are focused on structure and production optimization fields but with sustainability goals on the table the power plant design requires further time and focus. The impact of the power plant and propulsion systems selection in costs, safety or emissions is strong enough to have it into consideration in an individual box each new project with the correspondent variables link to the overall ship design.

To evaluate different power plant combinations it is done a quick overview on the existing solutions to be installed on board, analysing more in detailed the ones first inserted into the present algorithm, diesel Generating Sets (Gensets) and batteries. Fuel cells, super-capacitors, dual fuel engines or gas turbine installation are briefly described in them key aspects and state of the art inside the maritime sector. Table 3 enumerates the main existing alternatives in the market not including gas turbines, neither emissions reduction technologies, e.g. scrubbers. The correspondent electrical system reconfiguration each combination selected is targeted in future steps.

Table 3: Exsisting alternatives in the market for the power plant configuration

Selection 1	Selection 2	Further Classification	
Fuel Class	***Machinery Selection***	***Propulstion Type***	***Electrical System Topology***
HFO	Engine	Electrical	DC main distribution
Marine Diesel	Dual Fuel Engine	Mechanical	AC main distribution
Biodiesel	Genset		
Methanol	Battery		
Hydrogen	Fuel Cell		
Amonia	Supercapacitor		
External Charge			
LNG			

In addition, existing ship propulsion systems, linked with the available energy sources, are listed in Figure 5. Mechanical propulsion is conceptually linked from this notation with engines installation, either dual fuel or diesel engines which could evolve to hybrid propulsion systems if part of the energy generated is recovered or re-used, e.i. power take-in/off, via energy storage elements insertion or additional generators (shaft generators). The electrical propulsion system, defined by the use of electrical motors to cover the main propulsion, which commonly includes podded propulsion, [28], can be linked with Gensets power source installation and the rest of energy sources out of engines definition in this project, which is directly used to identify mechanical propulsion. Both AC and DC electrical motors are available options when selecting electrical propulsion and will be dependent on the electrical system requirements of stability and power levels among other factors under research as the grid distribution strategy. Azipods, fixed pitch propellers which rotates 360 degrees, have been much implemented within the yacht and offshore sectors and an emerging trend for larger vessels as the new Olendorff's newbuilds bulk carrier solution, which inside an "eco" newbuildings project since 2014, integrates two 1,9MW Azipod units from ABB to ensure lower emissions via fuel consumption reduction in a diesel-electric power plant, [31].

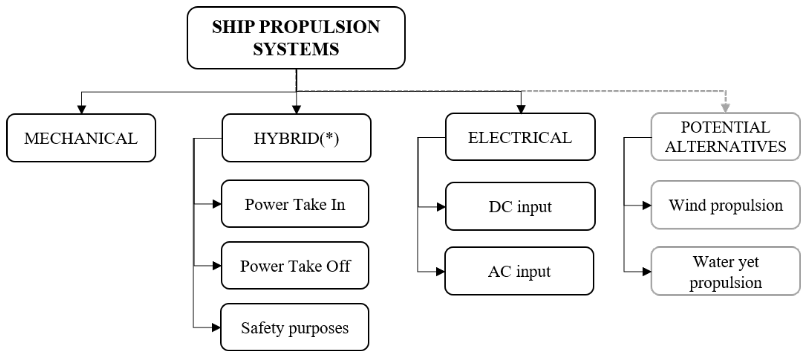


Figure 5: Existing ship propulsion systems, [25]

Every engine in the market is considered to comply with MARPOL 76/78 Annex VI restrictions, thus, it is considered to have the Engine International Air Pollution Prevention Certificate issued. No constraints referring this compliance will be introduce into the algorithm of analysis. Every marine diesel engine, with an output > 130 [kW], operating inside the North American ECA and the US Caribbean Sea ECA, and produced and installed from the first of 2016, will already comply with Tier III emission standards. From the first of 2021 it will be applicable inwards Baltic sea and North sea. If the engine does not comply with this regulations and the rest of the individual restrictions, including local ones, already stipulated by regulation it will not be included in the database of the algorithm.

Following MARPOL's Convention every ship under the specified conditions, after an initial or renewal survey and a specified period of time on duty, must have the endorsement of the following certificates:

1. Engine International Air Pollution Prevention (EIAPP) Certificate.
2. International Energy Efficiency Certificate
3. Statement of Compliance - Fuel Oil Consumption Reporting

Diesel Generating Sets:

The best way to extract the state of the art of the existing marine diesel engines for open source variables identification is taking one of the most commonly used brands of marine engines manufacturing as it is Caterpillar Marine Power systems. Its portfolio classifies engines for specific application considering the expected operational profile of them once installed. This consideration is translated into the operational load profile of the ship. Once different brands are analysed in future work an extraction of generic variables to consider for a first application filter of the machinery is essential for the proposed algorithm. Table 4 includes the different variables CAT brand considers when selecting a marine engine for installation based on the expected performance.

Considering the case study presented in Section 4 a Diesel Electric propulsion with electric drives would be the engine class consider when evaluating different Gensets sizing from Caterpillar for the present project. An expected maximum 10% overloading for a maximum of 1 hour out of 12 and a maximum of 25 hours per year is fulfilled if considering the load profile of the analysed 44 days of operation in Section 3.1. Unlimited hours per year is also an advantage for the Emergency Response and Rescue Vessel under analysis together with the wide margin for oscillating loads from 0 to 70% of the rated power.

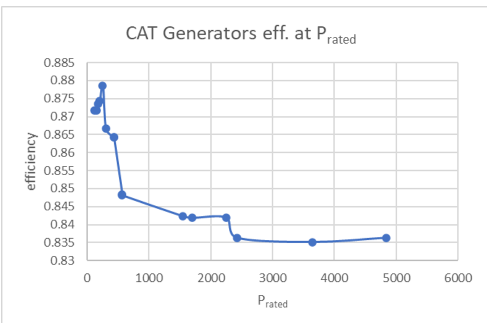
Table 4: Caterpillar marine engines classification for expected performance

Marine Rating , Propulsion Engines service		A unrestricted continuous	B heavy duty	C (MC) maximum continuous	C (FCVR) maximum continuous	D intermintent duty	E high performance	DEP diesel electric propulsion, electric drive
% of the total operating hours at a rated power	%	100	80	50	85	16	8	10% overload for max 1h out of 12h and max. of 25h per year
max. hours per year	hours	8000	5000	2000	2000	1000	250	unlimited
min hours per year	hours	5000	3000	4000	4000	3000	1000	unlimited
oscillated $load_{min}$	%	80	40	20	0	0	0	0
oscillated $load_{max}$	%	100	80	80	50	50	30	70
min. TBO				20000				
max. TBO				25000				
work over MCR, time limit			1					
work over MCR, time between			8.3-12					

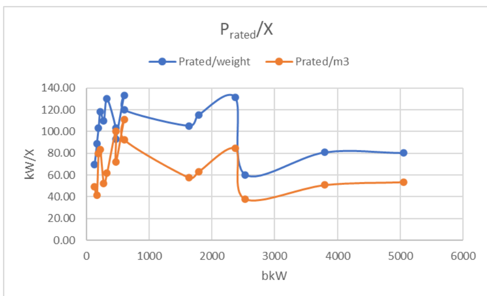
Table 5 gathers the existing CAT marine Gensets models, from 129 bkW to 5060 bkW, with its correspondent specifications from where to highlight for further analysis how the generator efficiency decreases when the power rating of the Set decreases, illustrated in Figure 6a. Figure 6b includes the specific power of CAT engines selection for analysis from Table 5 where models C18 and 3516E have the higher power density, hence, they are able to deliver higher instantaneous power from reduced installed space or weight. **Then, engine C18 is included to further test the algorithm with the case study defined in Section 4 together with the currently installed older marine engines CAT C32 and CAT 3516TAC**.

Table 5: Existing CAT Gensets - General Specifications

Gensets Models (current)						GENERAL								Engines Models
MODEL	P_{rated}			Generator	$speed_N$	***fc* at P_{rated} (100%)**	TIER	Application	Weight	Length	Width	Height	Cooling	
	bkW	*kVA*	*ekW@.8pf*	*eff. at P_{rated}*	*rpm*	*g/bkW-hr*	*IMO*		*kg*	*mm*	*mm*	*mm*		
C7.1	129	148	118.4	0.872	1800	237.4	II/III	auxiliary	1850	2175	956	1263	keel	CAT
	163.9	188	150.4	0.872	1800	226.2	II/III	auxiliary	1850	2444	986	1651	keel	CAT
	191.3	219	175.2	0.874	1800	221.9	II/III	auxiliary	1850	1984	956	1263	keel	CAT
	218.6	250	200	0.874	1800	219.5	II/III	auxiliary	1850	2175	956	1263	keel	CAT
C9.3	275	313	250.4	0.879	1800	216.4	II/III	auxiliary	2500	2366	1550	1436	keel	CAT
	325	375	300	0.867	1800	213	II/III	auxiliary	2500	2366	1550	1436	keel	CAT
C18	465	538	430.4	0.864	1800	215.1	II/III	auxiliary	4500	3050	1090	1396	keel	Stamford
	465	538	430.4	0.864	1800	220.2	II/III	propulsion	5000	3195	1274	1589	keel	Marelli
	599	706	564.8	0.848	1800	214	II/III	auxiliary	4500	3360	1091	1473	keel	CAT
	599	706.25	565	0.848	1800	214	II/III	propulsion	5000	3195	1274	1589	keel	Marelli
3512E	1632	1937.5	1550	0.842	1800	202.4	II/III	propulstion	15500	5399	2179	2400	keel	Avk
	1789	2125	1700	0.842	1800	200.9	II/III	propulstion	15500	5399	2179	2400	keel	Avk
3516E	2368	2812.5	2250	0.842	1800	204.3	II/III	variable speed	18000	5838	2066	2321	keel	Avk
C280-8	2530	3025	2420	0.836	900	198.5	II/III	propulstion	41920	8191	2104	3862	Sep./Combined	Yard Supply
C280-12	3800	4550	3640	0.835	900	196.3	II/III	propulstion	47000	7921	2347	4008	Sep./Combined	Yard Supply
C280-16	5060	6050	4840	0.836	900	190.7	II/III	propulstion	63105	9080	2589	4012	Sep./Combined	Yard Supply



(a) CAT Generators efficiency VS P_{rated}



(b) Specific Power CAT engines selection

Figure 6: Engines Data Analysis

In addition to the present data, which is open source, neither power response curves nor fuel consumption or emissions output measurements are open to public, hence for the present approach similar size engines from MAN marine engines with the project specifications sheets are used. The last part of data input required from diesel engines is the one from the ECU controls when the owner wants to make the approach more accurate, limiting the power response of the machinery also to those parameters of control commonly linked with safety more than energy consumption optimization. NO_X, CO, HC and PM are commonly measured from diesel engines following EPA CFR 40 and ISO8178-1. Data shown in Table 3 is based on steady state operating conditions of 77^oF, 28.42 in HG and number 2 diesel fuel with LHV of 18,390 btu/lb.

Batteries:

Nowadays, battery packs on board are not just considered for emergency purposes and they started to be installed for electrical system stabilization, load leveling or peak saving purposes together with the increasing research and development of Energy Management Systems, identified in the market by different industry steps as the one from Kongsberg Digital in 2021 adding Recogni A.S. as a new partner to the Kognifai Marketplace with its Blue Power EMS, [19].

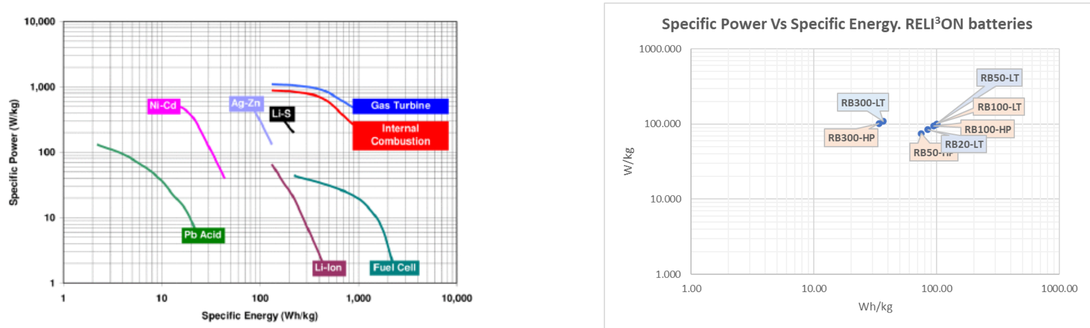
One of the documents which best analysis the state of the art of electrical energy storage elements for ships, including batteries, is the study carried out by the European Maritime Safety Agency (EMSA) reported by DNV in 2020, [14]. There, six functional roles for battery systems in ships installations are defined:

1. **Spinning reserve:** As a backup for installed generators, hence number of generators online reduced. It allows to reduce system redundancy levels.
2. **Peak Shaving:** As a buffer to avoid engines overloading conditions and leveling its charging point. They mainly absorbs energy to avoid overloading conditions.
3. **Optimise load:** It aims a cost optimization via maintenance volume reduction by running the rotatory machinery at an optimum working point. They slightly change the operating point of the generators to make them work under optimum ranges.
4. **Immediate power:** Instantaneous power delivery supporting generators. Similarly to peak shaving avoids overloading but, this time, they allows generators to achieve unmanned loads of higher sudden power during reduced time periods which can cause system instabilities or even damages.
5. **Harvest energy:** Mainly energy recovery purposes from hard operation activities and energy accommodation from renewable.
6. **Backup power:** Power back up provider for failure or fault conditions with elements as Uninterruptible Power Supplies for safety purposes.

Offshore Supply Vessels are reported in [14] as vessels with low power and energy needs for backup and with 5-20% of fuel savings and a payback time of 2 to 5 years when installing batteries, which are commonly used for DP-Spinning reserve. The document registers high C-rates when using batteries with low number of cycles at a nominal power release. Hence, Nikel (NMC), Lithium-Iron (LFP) and Lithium-Titane batteries are commonly used for OSV.

The study from EMSA in [14] highlights three different type of gaps for further improvement and development, the Legal/Regulatory(L), Harmonization(H), and Knowledge(K) and the last two ones are the why answer of the starting point of the present project.

When considering power plant preliminary design some of the most meaningful variables for evaluation are specific power and energy among the energy producers. Figure 7a includes these values from *Farmer 2020,* reported in [14]. It is not clearly defined how to calculate the value for these variables, some texts relay on simplified calculations with nominal voltage and nominal capacity batteries specifications while other texts go one step forward calculating the integral of $V(t) * A$ function, up to the voltage cut off time, even establishing dependencies with C-rate values. As long as the valuable information is taken from comparative terms Figure 7b illustrates the simplified calculation for seven different Lithium Iron batteries, from $RELI^3ON$ brand, used in the present project and grouped in low temperature and high temperature working conditions.



(a) Different batteries chemistry compared with internal combustion and gas turbines

(b) 7 different Lithium Ion batteries

Figure 7: Specific Energy and Power densities

The extraction from the present and brief overview of different power plant energy producers aspects to consider when sizing the power plant includes the expectation of higher space and weight requirements to supply the same amount of instantaneous power from batteries and fuel cells but also the advantage from hydrogen when considering energy density in comparison with marine diesel, from around 33 kWh/h for hydrogen to around 12 kWh/kg for marine diesel. The scenario is complex but it requires to evaluate how much the sector is able to invest in order to compensate for propulsion costs increment, including new safety measures, materials or further research on re-shaping the whole ship design project.

2.3 Curve fitting techniques

When great amount of real data is expected to be processed via computational tools it is required to familiarized the environment with the existing techniques for curve fitting purposes. This allows the work to link different environments via internal functions which could be improved among time with further training, if its structure settings are under conditions, or further analysis an new functions inclusion, if they are fixed by default.

Nowadays curve fitting softwares are able to process the data and fit the proper function to a specific input data, e.g. GraphPad's Prism, GitHub's SciDAVis, SigmaPlot or TriLookup. Matlab software and code is used for the present project so 2D data input curve fitting tools from Matlab are presented in Figure 8 not including smoothing methods, previous or post curve fitting process.

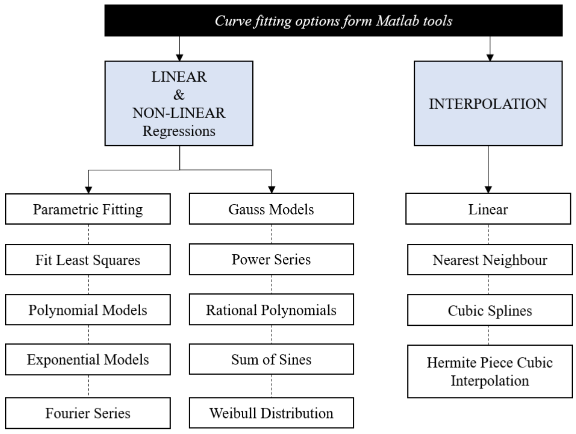


Figure 8: Curve fitting methods from Matlab

Parametric fitting is mostly applied to physical environments from where a mathematical parametric model is required to extract the deterministic component. The deterministic component of the equation or parametric model cannot be determined from the data with high accuracy, then, uncertainty of the calculation must be evaluated. The random component is usually linked with the error associated with the data considering data equal to deterministic component (parametric model) plus random component (data error). This method involves finding coefficients for one or more models to which you want to fit data.

Least Squares fitting is used to estimate the coefficients of a parametric model by minimizing the least squares (sum of squares of the residual values), being the residual value for the i-th data point r_i, the difference between the value of the observed response y_i and the value of the fitted response $\hat{y}_i$. This residual value is identified as the error associated with the data. Therefore the parametric model must be first selected to further estimate the coefficients.

Polynomial Models fitting in Matlab are given by:

$$y = \sum_{i=1}^{n+1} p_i x^{n+1-i} \tag{4}$$

They are used for simple empirical models, an interpolation or extrapolation, data characterization or global adjustment. It uses a lineal adjustment simplifying the process but high degree adjustments becomes unstable. One interesting point to reduce data instability is to center the mean to the 0 value and to make the standard deviation equal to 1 (center and scale option). Rational polynomials, as rational mathematical models illustrated in 5, can be considered to be used when the data structure becomes complex considering the risk of instability when the denominator is around 0.

$$y = \frac{\sum_{i=1}^{n+1} p_i x^{n+1-i}}{x_m + \sum_{i=1}^{m} q_i x^{m-1}} \tag{5}$$

Exponential Models fitting are commonly used when the change rate is proportional to the initial value of the quantity.

Following the same way Matlab gives different models to be also selected manually including Fourier series, Gaussian models, power series, sum of sines or the Weibull distribution model.

To estimate the coefficients fit different methods have been proposed, highlighting the well known

Levenberg-Marquardt algorithm.

Levenberg-Marquardt algorithm is usually used together with the least-squares curve fitting problem presented as a given set of m empirical pairs (x_i,y_i) of independent and dependent variables where to find the parameters β of the model curve f(x,β) so that the sum of the squares of the deviations S(β) is minimized:

$$\hat{\beta} \in argmin_{\beta} S(\beta) \equiv argmin_{\beta} \sum_{i=1}^{m} [y_i - f(x_i, \beta)]]^2 \tag{6}$$

Levenberg-Marquardt algorithm is an iterative procedure which starts with an initial guess for the parameter vector β replaced each iteration step by a new estimate β + δ. To determine δ, f(x_i, β + δ) is approximated by its linearization:

$$f(x_i, \beta + \delta) \approx f(x_i, \beta) J_i \delta \tag{7}$$

Where the gradient of f with respect to β is:

$$J_i = \frac{\partial f(x_i, \beta)}{\partial \beta} \tag{8}$$

Thus, the sum of square deviations ($S(\beta)$) has its minimum at a zero gradient with respect to β. The first order approximation from 6 is expressed as:

$$S(\beta + \delta) \approx \sum_{i=1}^{m} [y_i - f(x_i, \beta) - J_i \delta]]^2 \tag{9}$$

By applying vector notation, the derivation of $S(\beta + \delta)$ and setting the result to zero, to get the minimum, the resulting expression leads into:

$$(J^T J) \approx J^T [y - f(\beta)] \; (Gauss - Newton\, method) \tag{10}$$

a set of n linear equations which can be solved for δ. But Levenberg introduced a damping factor to be adjusted each iteration to faster approach the minimum.

When evaluating these existing tools to be used for the present algorithm two valuable points have been extracted:

1. *The model (parametric, polynomial, exponential..) must be first selected for the whole data sample introduced.*
2. *To reduce data instability for polynomial models fitting the mean could be centered to 0 and the standard deviation be set to 1.*

Then, further research on dynamical curve fitting methods or advanced curve fitting techniques is presented.

Regarding the first point extracted, the best fit in the mathematical model selection step, there is no generic way to select automatically the best function each new data insertion. The commonly used method goes to manual evaluation by computing each function type and the correspondent error, e.g. least squares fitting method. There are also existing softwares which well perform the task such as LAB fit which includes nonlinear regressions for curve fitting or Levenberg-Marquardt algorithm among others.

An interesting approach to evaluate the quality of a selected statistical model for a given set of data among others, was the one presented for Hirotugu Akaike in 1974 as *New Look at the Statistical Model Identification*, [2]. Nevertheless, and once more, the approach is oriented to time series data with physical meaning, which carries the research to evaluate multivariate adaptive regressions which model selection result will comply with different variables performance. Ship design functions linking different design variables are, par excellence, multivariate regressions with no explicit physical meaning.

Some statistical methods could be also used for curve fitting as regression analysis, highlighting the well known multivariate adaptive regression spline, a non-parametric regression technique.

Multivariate adaptive regression spline was presented in 1991 as an invited paper to the The Annals of Statistics, [15], for flexible regression modeling of high dimensional data. In the paper this problem is issued as the searching for an adequate approximation a function of several to many variables given only the value of the function at different various points in the dependent variable space, tackled by several disciplines, applied mathematics with multivariate function approximations, statistics with non parametric multiple regressions and computer science and engineering with statistical learning neural networks. The computational cost from all them is exceeds the expected approach to apply for the present algorithm in the Relational Data Table.

In [36] curve fitting task is tackled as shortest-path type problem and proposes a polynomial-time algorithm to construct a monotone step-wise curve that minimizes the sum of squared errors with respect to a cloud of data points. The approach is interesting to be analyzed due to its defined constraints settings, from the maximum number of steps to the minimum step length to procure the trade off between required accuracy and maximum computational time.

3 Methodology

From a general perspective seven different power plant design modes are defined from the combination of the different existing alternatives mentioned in 2.2. They split the groups considering the energy source and the technology for energy production thus extracting the following groups of analysis:

1. **Full Electric Mode (FEM):** The present mode includes just storage elements which requires from an external source to be refilled. At the beginning they are going to be a favourable solution considering no external energy cycle analysis and limiting optimum environments to evaluate the closed cycle on-board. Batteries and super capacitors consolidate the group.
2. **Fossil Fuels Hybrid Mode (FFHM):** The present mode includes all technologies running with fossil fuels in combination with storage elements. The elements from FEM and diesel, fuel-oil or benzine engines close the group.
3. **Fossil Fuels Mode (FFM):** The present mode includes all technologies running with fossil fuels, mentioned in FFHM, without the add-on storage elements.
4. **Alternative Fuels Hybrid Mode (AFHM):** The present mode includes all technologies running fully or partially with alternative fuels, considering as alternative fuels all non-fossil fuels used to reduce emissions and enhance clean energy solutions. The modes include, for instance, dual fuel engines, fuel cells or engines running with bio-fuels, in combination with storage elements from FEM.
5. **Alternative Fuels Mode (AFM):** The present mode includes all components from AFHM without storage elements contribution.
6. **Gas Turbines Hybrid Mode (GTHM):** The present mode targets gas turbine installations on board individually, due to the complexity and challenges of the present systems in the maritime sector, in combination with storage elements.
7. **Gas Turbines Mode (GTM):** The present mode targets gas turbine installations on board individually without the contribution of storage elements.

Each of them evaluates the feasible arrangements with the rest of the power and propulsion system, e.g. mechanical or electrical propulsion, electrical systems design, control methods implementation...

The presented methodology includes three main steps for development:

1. **Holding structure:** the holding structure is ready to include all new machinery input, considering that a little reformulation could be required each new element insertion but minimizing the impact from that.
2. **Data processing:** the data processing environment includes for this scope the analysis on the load profile insertion, the energy measurement estimated error, the relational data table structure settings and inner data treatment and the capacity reduction per cycle estimation methodology for all storage elements included in the algorithm.

3. **First modes settings:** to approach a first structure for the algorithm three potential combinations from Figure 9 are selected. The selection includes a Full Electric Mode (FEM), number 17 in the figure and a single battery bank solution for energy production; a Fossil Fuels Hybrid Mode (FFHM) evaluating the combination number 10 from the figure with a Gensets package combined with battery bank source of energy; and the Fossil Fuels Mode (FFM) considering the only use of Generating Sets, number 9 in the Figure.

Figure 9 presents the expected combos to be inserted in future approaches to extend the algorithm potential.

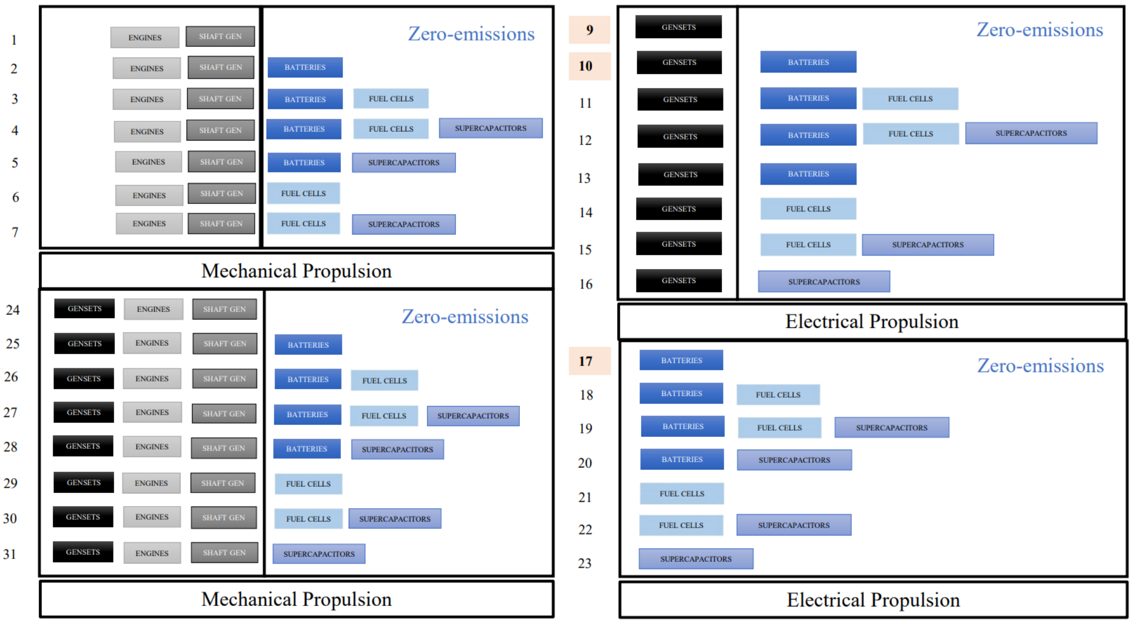


Figure 9: Power Generation Existing Combos

The algorithm is expected to introduce the estimated or measured operational behaviour of the ship, via load profile insertion into the preliminary design evaluation of the power plant, considering the available components from the market. The algorithm structure presents different modules, which are roughly defined in the present project but open to be targeted in future work for further development. The modules include:

- **Data Input Environment:**

  This module is the one of the most important holding sets to success on the idea of automating a procedure for a generic power plant design inside the shipping sector. The wide variety of scenarios requires from a flexible algorithm able to be shaped with different data environments with results adjusted to the project needs. Figure 10 defines the first data input environment approach, splitting the box into different packages of data which values will be dependent on the project specifications. One side the ship type will be defined by its load profile and linked with the selected rules and regulations package structure to be inserted also in the algorithm. On the other side, the existing machinery, ready for installation in the market comes from a common data storage which could be defined as a Data-Base in future work enhancing zero emissions solutions. Additionally the nature of the project must be inserted in another package where to define aspects as if it is a retrofit with the correspondent data from the current installation or a new construction vessel mixed with the client wishes on the project results to take them into account. Finally a Relational Data Table establishes the link from the overall ship design variables to the inner power plant design variables and parameters selection and its impact back to the design. All these data is introduced into the core of the algorithm divided in two stages.

All the above described environment, defined in Figure 10, is inserted previous algorithm run to a data processing environment which main essence relays on a proper development of an application filter and a good estimation of the maximum expected error.

- **Algorithm Structure:**

  The core structure of the algorithm includes two main environments. The first one, the feasibility evaluation, is defined by different binary statements. It is considered out of the optimization environment for reducing computational time in a huge objective function which could have considered the binary matrices as constraints for a multi-objective mixed integer non-linear programming. In contrast, the number of potential solutions to evaluate for optimization is first reduced and the optimization environment can by simplified to a multi-objective linear optimization program with client wishes and regulations limits as costs, safety or emissions output constraints. The feasibility is defined from ship design constraints, mainly given from the project nature input data, as weight, space and autonomy and operational constraints, mainly given by the machinery specifications input and system arrangements, with the system maximum power response and system speed of response. Finally, the feasible scope of solutions is expected to be evaluated among costs safety and emissions with its correspondent weighting factors.

- **Output environment:**

  As an output it is expected to have a scope of optimum solutions from the updated market perspective from the input environment, defined in its main characteristics, e.g. size, number or fuel type. Then following a proper estimation of the load profile the operational ranges which makes the solution optimum is an important part of the output linked with with each individual solution proposal. Key Design Indexes (KDI) are part of the solution description, not just for the algorithm performance testing in preliminary phases but also for the design evaluation, aiming to become readable for the user. To procure this readability a software development is part of future work expectations with a user manual. Design power plant guidelines extracted after algorithm consolidation are expected once a common pattern for design is well identify by training and redefining the algorithm for different case studies.

  Considering the presented output, a control bandwidth to be inserted in a centralized EMS could be easily defined also analyzing the impact of going out the optimum bandwidths. This control constraints for a specific solution can be then targeted in a more detailed system modelling, e.g. a data driven model or digital twin, where to further define the control settings and give feedback to the present platform about controlability and robustness of the solution, system reliability or maintenance costs estimation.

  It is important to mention that it is essential a first analysis on the available machinery open-source data and the additional data which would be required to analyze the solution under real margins. This should be first clarify when presenting the final algorithm settings to potential users.

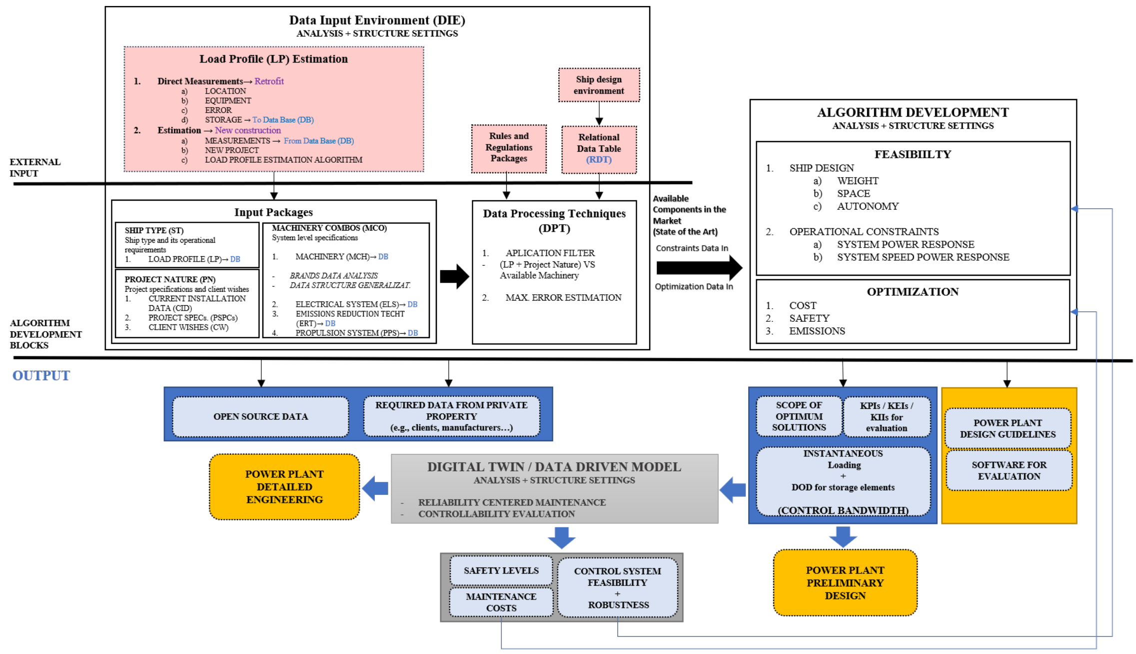


Figure 10: Full Project Structure

By now the solution is elaborated in Matlab code, considering this code closer to Simulink environments of modelling and systems simulation with controllers design purposes which can be redefined as python packages from Matlab functions later on, if required, or to be adapted to Open Platform Communications for real-time plant data between control devices via OPC toolbox from Matlab. This is the way to keep the algorithm closer to control systems design environments.

3.1 Data Processing

The present section describes data input treatment, computing and calculus error tracks linked with data input filters aiming a preliminary design perspective with affordable computing tools requirements and accurate enough output power plant designs which considers expected operational behaviour in terms of power requirements among time.

At this scope data processing analysis includes:

- Load profile data extraction.
- Relational Data Table (RDT), data treatment.
- Energy computing error. It includes each energy producer type convenient calculation.
- Storage elements capacity reduction per cycle, calculation method and consequent expected deviation (error).
- Application filter.

3.1.1 Load profile

One of the key aspects for the present algorithm is the insertion of a proper load profile estimation for the ship under analysis. By running the algorithm over the load profile sample a scope of optimum solutions for the power plant design is extracted.

Additionally, and looking for computational expenses reduction, each new case study extracts also a group of load profile description indexes to be evaluated versus estimated system design results. With these indexes and after working with different case studies through the algorithm, it will be able to directly scope a range of solutions which bests suits with the load profile characteristics inserted without the need of running the sample through the feasibility or optimization environment. This step of analysis could be considered as artificial intelligence or machine learning insertion considering the algorithm ready to perform under reduced computational time with similar accuracy levels to the proposed bottom structure of calculus via relational data table.

Data from the load profile is inserted as a discrete data sample with specific time step registered, hence, it already includes measurements error. The load profile data is required to be measured at the output of the energy producers which means to include the overall efficiency of the system in it. This considerations requires form a thoughtful analysis of the load profile estimation inserted which should be done for a specific system characteristics. From this step the relevance of having feedback from high accuracy models for specific system typologies testing together with data measurements from existing ships. The algorithm becomes a tool for storage and processing of data measurements and high accuracy model tests output to get further scoped solutions scenario to be considered each new power plant design projected.

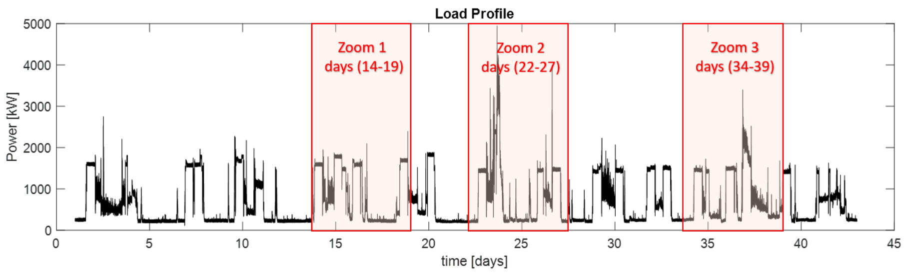


Figure 11: Load Profile inserted for analysis

Figure 11 illustrates the load profile charged for the case study selected and defined in Section 4. For the present scope the load profile estimation and pattern recognition for power plant design purposes is reduced into a manual selection of 3 different critical zones for study from the total load profile, considering higher instantaneous power and energy demand. Future scopes will include automatic recognition for design optimization.

Table 6: Load Profile Indexes for analysis

	from 44 days register	LP ranges (days)	44	14-19	22-27	34-39
Instantaneous Power	$(p_i)_{max}$	maximum	4945.00	2394.00	4945.00	3400.00
	$(p_i)_{min}$	minimum	115.00	182.00	176.00	179.00
	$(p_i)_{mean}$	mean	695.84	881.86	839.35	828.51
	$(p_{i90})_{\%}$	% at 90% or more of $(p_i)_{max}$	0.00	0.00	0.00	0.00
	$(p_{i70-90})_{\%}$	% at 70% - 90% of $(p_i)_{max}$	0.06	14.26	0.49	0.14
	$(p_{i30-70})_{\%}$	% at 30% - 70% of $(p_i)_{max}$	14.81	37.12	10.48	34.20
	$(p_{i30})_{\%}$	% at 30% or less of $(p_i)_{max}$	85.13	48.62	89.02	65.64
	$(p_{neg})_{\%}$	% at neg p_i	0.00	0.00	0.00	0.00
Power Drop	$\Delta\ (p_{i-pos})_{max}$	max. R+	2107.00	1626.00	2107.00	1399.00
	$\Delta\ (p_{i-neg})_{max}$	max. R-	2475.00	1304.00	2475.00	1369.00
Power Drop Accumulated	$\Delta\ (p_{acc-pos})_{max}$	max. R+	3363.00	2020.00	3363.00	1674.00
	$\Delta\ (p_{acc-neg})_{max}$	max. R-	3014.00	1687.00	3014.00	1369.00
Speed Accumulated	$(v_{acc})_{max}$	maximum	293.60	325.20	293.60	279.80
	$(v_{acc})_{min}$	minimum	495.00	260.80	495.00	273.80
	$(v_{acc})_{mean}$	mean	0.07	0.08	0.12	0.05
	$(v_{acc90})_{\%}$	% at 90% or more of $(v_i)_{max}$	0.00	0.00	0.00	0.00
	$(v_{acc70-90})_{\%}$	% at 70% - 90% of $(v_i)_{max}$	0.00	0.00	0.00	0.00
	$(v_{acc30-70})_{\%}$	% at 30% - 70% of $(v_i)_{max}$	0.02	0.01	0.08	0.03
	$(v_{acc30})_{\%}$	% at 30% or less of $(v_i)_{max}$	47.58	47.54	46.77	48.77
	$(v_{acc-neg})_{\%}$	% at neg (v_i)	52.06	52.14	52.77	50.99
Acceleration Accumulated	$(v_{acc})_{max}$	maximum	58.72	65.04	58.72	55.96
	$(v_{acc})_{min}$	minimum	99.00	52.16	99.00	54.76
	$(v_{acc})_{mean}$	mean	0.01	0.01	0.01	0.01
Energy	$(E_{acc})_{max}$	maximum	2.53E+09	3.81E+08	3.63E+08	3.58E+08
	$(E_{aut-1h})_{max}$	maximum; autonomy of 3600h	1.21E+07	6.44E+06	1.21E+07	8.01E+06
	$(E_{aut-1})_{max}$	maximum; autonomy of 1d	1.45E+08	1.09E+08	1.45E+08	1.09E+08
	$(E_{aut-3})_{max}$	maximum; autonomy of 3d	2.48E+08	2.78E+08	2.22E+08	2.34E+08
	$(E_{aut-5})_{max}$	maximum; autonomy of 5d	3.38E+08	3.81E+08	3.63E+08	3.58E+08

Table 6 includes for analysis different indexes which reproduce the load profile distribution in terms of power and speed or acceleration response in single steps or accumulated terms, considering as accumulated values the ones including the whole charging or discharging steps over time. These terms are conceptualized in Figure 12.

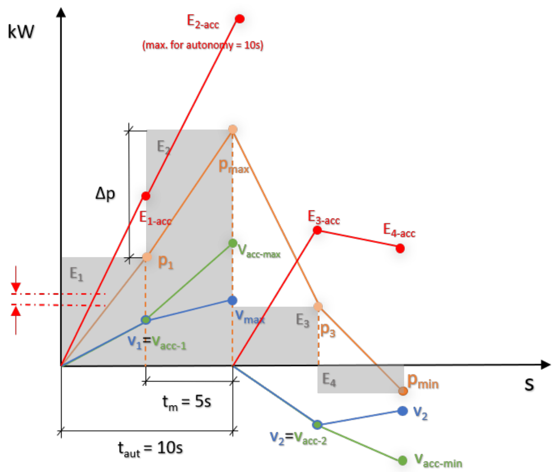


Figure 12: Load Profile indexes conceptualization

The indexes included in Table 6 are used to evaluate, for this scope, the risk on optimizing the system design over a reduced power measurements sample, hence, highly reducing computational costs. These results illustrates in red the values under risk of, while full filling the scoped sample requirements the design could not comply with the requirements for the overall load profile registered. By including indexes which identify the percentage from the maximum power demand each power measurement step, the power distribution of the sample is described each range selected.

Considering this evaluation, the load profile registered from day 22 to day 27 could be considered as critical as the whole load profile sample. For the mentioned sample range, the instantaneous power steps registered at the rage of 30% to 70% the maximum instantaneous power are lightly reduced but, higher instantaneous power steps are registered minimizing the impact of this reduction. This pattern is followed by the accumulated speed indexes, hence, also considering to comply with the whole load sample. Also in this time frame the maximum energy required per autonomy slot of 1 hour and 1, 3 or 5 days is similar than the one required for the overall sample with a bit risk under 3 days of autonomy requirements.

As a result of the test, the second rage selected from day 22 to day 27 is the one tested inside the algorithm for the presented case study in Section 4.

3.1.2 Relational Data Table

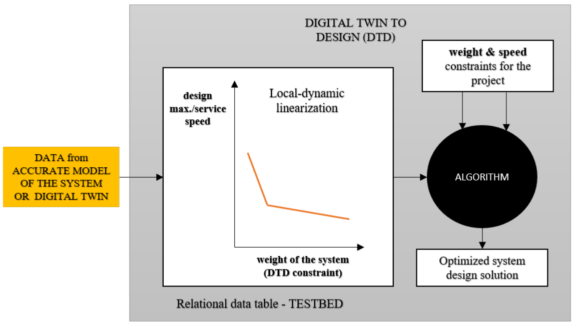


Figure 13: Relational Data Table conceptualization

All data introduced is discrete data and most of the error track is also based on the sampling time. Nevertheless, for introducing the project environment, e.g. ship type or project nature, it is required to select a proper methodology reflecting this data inside the power plant sizing environment. To do so a Relational Data Table structure is defined with the present case study but also re-defined and improved with new projects in future work. The way of computing this relations must be analysed to minimize computational time and maximize the accuracy of the results.

The present analysis focuses on the curve fitting method elaboration to process each ship design-power plant design data relation required to be established when sizing the power plant. The nature of this type of data is dependent on many other variables of the design, e.g. additional functions from one ship to other inside the main class, different equipment combinations or even differentiated hull shapes. As a consequence, the relational table must be updated with new designs to process new data and generate new and updated variables' linking functions and the holding approach is a piece-wise final function objective. As long as the functions have not necessary just physical meaning, they could include design or systems combination aspects, they are considered difficult to make them fit with an standard function model to proceed with a curve fitting regression method.

The analysis requires that non-linear and non-deterministic models are well fitted hence, to be carried out considering dynamical curve fitting techniques which best suits with non-standard functions types or a mix of some of them. Translated from the literature review in Section 2.3 the mathematical model or deterministic part of the curve fit must be first selected and this work aims to automatise this process minimizing computational time, proposing a multi-structure curve fitting following the basic principle presented in Figure 14 which concept is also illustrated in Figure 15.

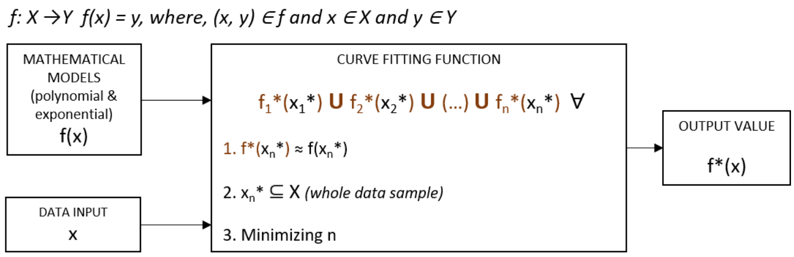


Figure 14: Multi-structure curve fitting basic principle

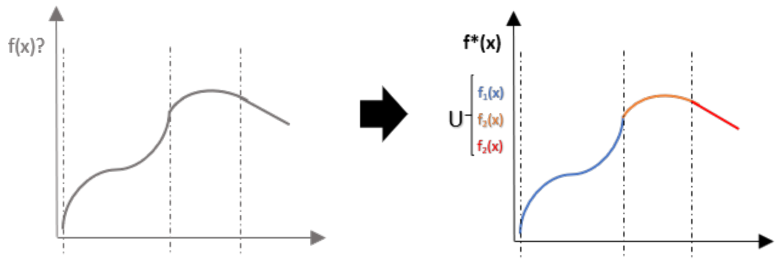


Figure 15: Multi-structure curve fitting concept

To explain the present issue it is presented an analogy with the Best Fit algorithm used in $C++$ code for memory management purposes. This algorithm allocates the smallest free partition which meets the requirement of the requesting process. To do so the whole memory block is evaluated to select the appropriate block for the process where to be allocated. The analogy identifies memory blocks as inserted function blocks which length, with its inherent final number of blocks, is one of the variables. The process is allocated into the smallest well suited memory block which, in the analogy presented, it is maximised, meaning that each function type is allocated in the biggest step length which well suits enough, considering as enough to comply with a determined maximum error constraint.

Variables:

- $\underline{Sl_{if}}$: inserted function step length, [vector] $\rightarrow Sn_{if}$ (n from Figure 14), number of steps.
- $\underline{\epsilon_{b_{max}}}$: maximum total error per box.
- $\underline{\epsilon_t}$: total error.

The aim of this curve fitting method is to reduce computational time from other approaches presented in the literature review but also to make it fit with the needs of the present project. The method is defined in 3 steps presented below.

1. **To define the mathematical generic models.**

   The algorithm requires from different mathematical models to be inserted and evaluated for the best fit solution. By now polynomial models up to 4th degree and exponential function, illustrated in Figure 16 are tested with different coefficients aiming to find the common pattern to be compared with the inserted cloud of data.

   Functions and ranges computing selection in Matlab to extract the graphs below:

- f_{cte}(x) = a
- f_1(x) = b x + a
- f_2(x) = c x^2 + b x + a
- f_3(x) = d x^3 + c x^2 + b x + a
- f_4(x) = e x^3 + d x^3 + c x^2 + b x + a
- f_5(x) = a e^x

Being, a = b = c = d = e = $v_x \in$ V s.t. x=[1,2,3,4] and V is an array of vectors exposed in a cascaded loop, to get all combination outputs, and defined as it follows:

$$V = \begin{cases} v_0 = -50 : 25 : 50 \\ v_1 = -1 : 0.5 : 1 \\ v_2 = 50 : 25 : 100 \\ v_3 = -100 : 25 : -50 \end{cases} \tag{11}$$

The above exposed vectors to test different coefficients each polynomial are computed for x = -100:10:100. The vector tests selection is done considering that, by increasing the number of x vector numbers, the computational cost increases when plotting the surfaces for evaluation and, by increasing the number of coefficients combination the computational cost of running the test algorithm highly increases, as expected due to the high number of loops defined to test each combination of them. For this approach small vector step sizes are disregarded considering them and its impact on the present approach in future work, meaning that coefficients lower than 0.5 are not included in the present explanation.

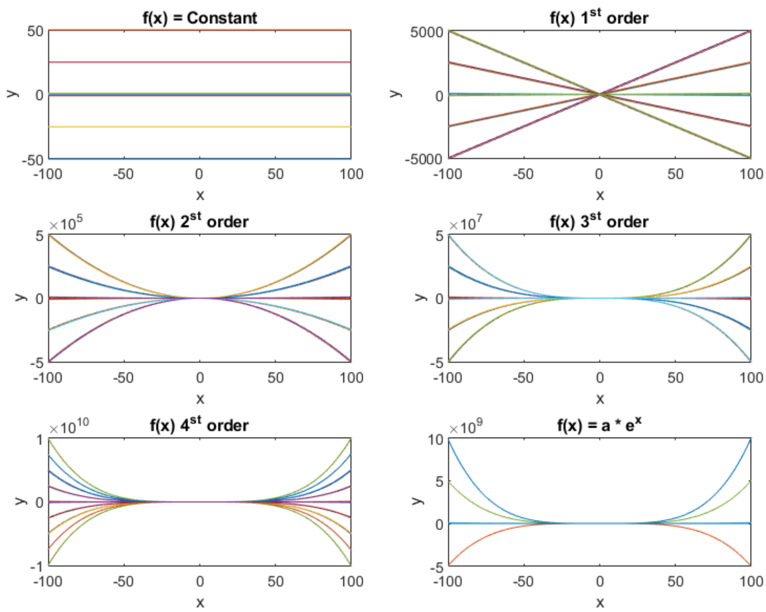


Figure 16: Curve fitting functions selection

2. **To extract each function common pattern.**

   Keeping in mind some extraction from the literature review appealing curve fitting methods regarding function mean centering to 0 and standard deviation settings to 1, this first analysis to find the common pattern each polynomial degree, disregarding the coefficients value, is done over the error from the function value at step measured i and the dynamical mean of the sample up to the same i value illustrated in equation 12.

For i=1:length(X):

$$Y(i) = f(x) \tag{12}$$

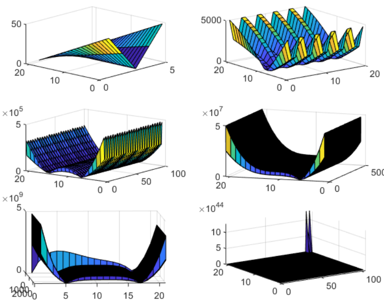
$$mean_{dyn}(i) = mean(Y(:))_i \tag{13}$$

$$mean_{error}(i) = abs(Y(i) - mean_{dyn}(i)) \tag{14}$$

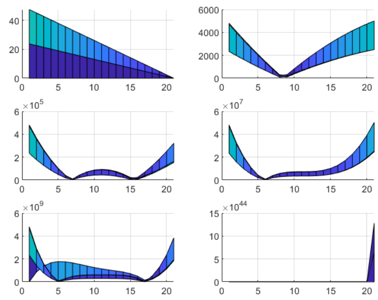
Being X the vector sample centered to 0.

By applying the presented formula each function for the already mentioned main vector tests for different coefficients combos and a specific X vector the goal is to find a common pattern not dependent on the coefficient selection to find first the best function fit, or mathematical model, from where to define the best coefficients fitting for each piece from a piece-wise function that it is required for this approach. For a first visual evaluation, all dynamical means error from equation 12, for all coefficients combos applied to the different functions selection, are plotted in a surface shape in Figure 2.

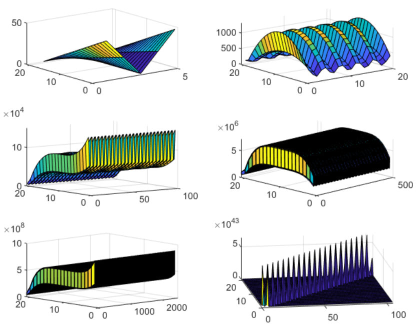
In Figure 2 constant values evaluation is useful help if the test evaluation is correctly computed. Ensuring so, first second and third order polynomials show common points each new coefficients combo, meaning that although they do not match, as expected, for all coefficients selection, they apparently show to match on having minimums repeatedly at the same location form the center of the sample, which is centered to 0 due to the x vector selection. This statement can be well appreciated in Figures 17b and 17d at 90 degrees view with the X step number for x axes in the graph (x_{vector}=-90 == x_{graph}=1).



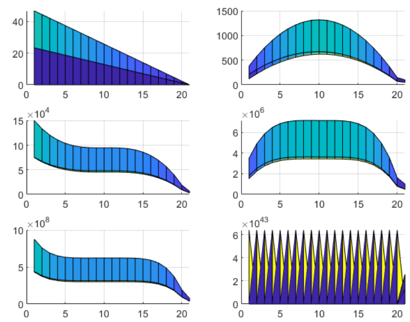
(a) Run 0, v_0, X=-100:10:100. From up-right to left down: 3D of mean error from f_{cte}, f_1, f_2, f_3, f_4, f_5



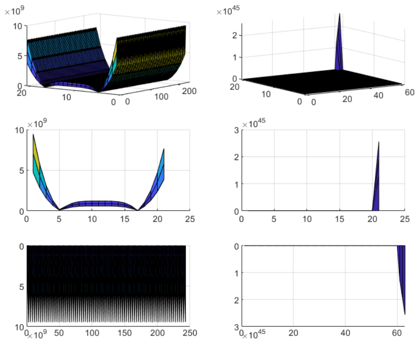
(b) Run 0, v_0, X=-100:10:100. From up-right to left down: 3D, 90 degrees of mean error from f_{cte}, f_1, f_2, f_3, f_4, f_5



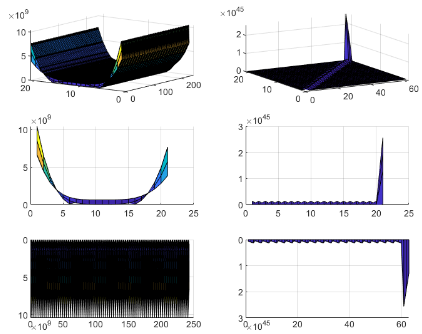
(c) Run 1, v_1, X=-1:0.5:1. From up-right to left down: 3D of mean error from f_{cte}, f_1, f_2, f_3, f_4, f_5



(d) Run 1, v_1, X=-1:0.5:1. From up-right to left down: 3D, 90 degrees of mean error from f_{cte}, f_1, f_2, f_3, f_4, f_5



(e) Run 2, v_2, X=-1:0.5:1; 1_{st} column: mean error from f_4 in 3D, 90 and 180 degrees; 2_{nd} column: mean error from f_5 in 3D, 90 and 180 degrees



(f) Run 3, v_3, X=-1:0.5:1; 1_{st} column: mean error from f_4 in 3D, 90 and 180 degrees; 2_{nd} column: mean error from f_5 in 3D, 90 and 180 degrees

Figure 17: Mean error shape from different coefficients selection for the 5 selected functions

From Figure it is also reflected how for x values lower than 1 the pattern changes but also tested how for centered to 0 x vectors the pattern keeps showing the minimums at the same specified locations as it is included in Table 7. Due to so, the present evaluation will discard x vector values with a sample step lower than 1.

3. **To define the multi-structure algorithm.**

4. **To test the algorithm for different non-linear & non-elementary functions.**

Table 7: Test results to identify the common pattern of each function type

Tests number/side = 11		VECTOR for combos	Number of Minimums (equal)		Minimums Location range *% of the sample displaced from center (aprox.)*			Comments
			left	right	left	right		
cte	**R0**	-50:25:50	1 & 11(one)	1 & 11(one)	0	100	CS	It goes to 0 one of the runs,
	R1	-1:0.5:1	1 & 11(one)	1 & 11(one)	0	100		counting for 10 minimums,
	R01	-100:25:100	1 & 11(one)	1 & 11(one)	0	100	CS	that value should be off interpretation
	R02	-200:50:200	1 & 11(one)	1 & 11(one)	0	100	CS	(coefficients == 0)
1st order	**R0**	-50:25:50	1	1	19 OR 28	9	CS	
	R1	-1:0.5:1	1	1	90	100		
	R01	-100:25:100	1	1	18 OR 27	9	CS	
	R02	-200:50:200	1	1	18 OR 27	9	CS	
2nd order	**R0**	-50:25:50	1	1	37	46 OR 55	CS	
	R1	-1:0.5:1	1	1	19	100		
	R01	-100:25:100	1	1	37	46 OR 55	CS	
	R02	-200:50:200	1	1	37	46 OR 55	CS	
3rd order	**R0**	-50:25:50	1	1	45	9	CS	
	R1	-1:0.5:1	1	1	91	100		
	R01	-100:25:100	1	1	45	9	CS	
	R02	-200:50:200	1	1	45	9	CS	
4rd order	**R0**	-50:25:50	1	1	55	64	CS	
	R1	-1:0.5:1	1	1	28	100		
	R2	50:25:100	1	1	55	64		
	R3	-100:25:-50	1	1	0 OR 46	9 OR 55		
	R01	-100:25:100	1	1	55	64	CS	
	R02	-200:50:200	1	1	55	64	CS	
Exponential	**R0**	-50:25:50	10-11	10-11	0-91	9-100	CS	
	R1	-1:0.5:1	10-11	10-11	0-91	9-100		More than one equal minimum,
	R2	50:25:100	10-11	10-11	0-91	9-100		no need to evaluate from this result the location
	R3	-100:25:-50	10-11	10-11	0-91	9-100		of the minimum,
	R01	-100:25:100	10-11	10-11	0-91	9-100	CS	but all combos' run follow the same pattern
	R02	-200:50:200	10-11	10-11	0-91	9-100	CS	

Table 8: Minimums location in percentile units from the center of the sample to both sides

	Minimum locations ranges out % of half sample from the center	
	left	**right**
cte	0	100
1st order	(18 OR 28)±2	9±2
2nd order	37±2	(46 OR 55)±2
3rd order	45±2	9±2
4th order	55±2	64±2
exponential	max = 91±2	min = 9±2

The last two steps keep out of scope in the presented document.

3.1.3 Energy measurements

The demanded energy at a specific time is calculated in terms of single power measurement each time step registered. From the single demanded energy each time step in the load profile the accumulated energy is calculated under specific requirements. When introducing storage elements into the algorithm these calculations becomes highly relevant. For the present scope the accumulated energy is calculated for:

- $E_{acc_{brc}}$: accumulated energy between recharges. Considering recharges at port or portable sources of electrical power from Offshore Service Units and estimated via minimum autonomy requirements.
- E_{acc_T}: Total accumulated energy among the whole load profile. It is calculated to be used in the first application filter, to identify a first classification which allows to reduce the scope of feasible solutions to be installed in the power plant.

Hence, the computational error of the energy measurement, ϵ_{Ec} is maximized and estimated each step of time registered as a function of the response time of the ship power system as illustrated in Figure 27. Then, the accumulated error is calculated from the summary of the single error at a specific time. A generic structure identifies t_{RD} as maximum time of response to load instantaneous power demand and t_{RS} as the minimum time to stop or reduce the loading from the power system. Both t_{RD} and t_{RS} could be a future target for analysis but simplified under some assumptions for the present scope.

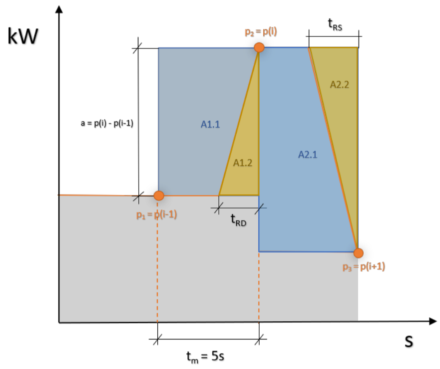


Figure 18: Energy Measurement Error Calculus

From Figure 27 blue areas are the representation of the maximized error calculated as it follows:

$$\epsilon_{Ec1/2} = A(1/2).1 - A(1/2).2 \tag{15}$$

$$\epsilon_{Ec1/2} = (\mid a \mid \times t_m) - \left(\frac{t_R \times \mid a \mid}{2}\right), \forall a \in \mathbb{R} \tag{16}$$

Where:

$$t_R = \frac{a}{v_{max(dis)}(NOEs)} = minimum\, machinery\, response\, time$$

$$a = p(i) - p(i-1)$$

$$t_m = \; measurements\, time\, step$$

$$j = energy\, producers\, type$$

$$NOEs = number\, of\, elements$$

Being v_{max} worse case scenario defined by the maximum current able to be delivered, or peak current (i_{peak}), each individual battery, and the minimum expected voltage as the BMS cut-off voltage ($V_{BMScut-off}$):

$$v_{max} = \frac{\sum_{j \in J} \left(V_{EMScut-off} \times I_{peak} \times NOEs\right)_j}{t_{RM}} \tag{17}$$

$$\epsilon_{Ec(1/2)} = (\mid a \mid \times t_m) - \left(\frac{\mid a \mid^2}{v_{max} \times 2}\right) \tag{18}$$

Where tRM is the minimum time to response of the machinery element considered, here the battery time to deliver the peak current, I_{peak}.

If inserting further elements it is not expected to conflict with the presented formulation due to each of them is pretended to be evaluated for the amount of energy analysed to deliver each of them, as a percentage of the total energy demand.

Additionally, the present error maximization assessment is able to conclude with an additional design index identifying performance feasibility of the power system, which means being able to cover the power demand from the inserted load profile. To do so, the algorithm must ensure compliance with $(v_{max(dis)})_{max}$ function of I_{peak} and $(t_R)_{min}$ with the load requirements, individually.

From equation 15, two deductions can be extracted in two decreasingly restrictive conditions:

1. 1. $t_R > t_m \rightarrow$ Non feasible.
2. 1. $V_{EMScut-off} \times I_{peak}(NOEs) > \Delta p(i) \rightarrow$ Non feasible.

If $\epsilon_{Ec1/2} < 0 \rightarrow \mathbf{A(1/2).2} > \mathbf{A(1/2).1} \rightarrow$:

1. 2. $\rightarrow min(t_R)$ feasibility check:

   $t_R = t_{RM}$

   $\left(\frac{t_{RM} \times |a|}{2}\right) > (|\ a\ | \times t_m) \rightarrow \frac{t_{RM}}{2} > t_m \rightarrow$ Non feasible.
2. 2. $\rightarrow max(i_{delivered})$ check via $max(v_{response})$:

   $\left(\frac{|a| \times t_{RM}}{2 \times V_{EMScut-off} \times I_{peak}(NOEs)}\right) > t_m \rightarrow$ Non feasible.

If the lasts conditions extraction is non-feasibility the test could be stopped there with a non-feasible result. If either 1.2 or 2.2, individually, results in non-feasible the solution is non-feasible due to not enough current supply or not enough time to system response. If further digging is required then either 1.1 or 1.2 solves the problem to identify the faulty variable for non-feasibility condition, t_R OR $p_{max}(v_{max})$.

Previous statements ensures non-feasibility but they do not ensure feasibility. The deduction requires for stronger assumptions to identify all non-feasible solutions. As it is expected, from deduction 1 and to ensure feasibility, the power system response time detriment is favourable to increase feasibility ranges. This could be done by increasing NOEs or installing batteries with smaller discharge times by default (usually smaller batteries). The evaluation follows the line in Figure 19.

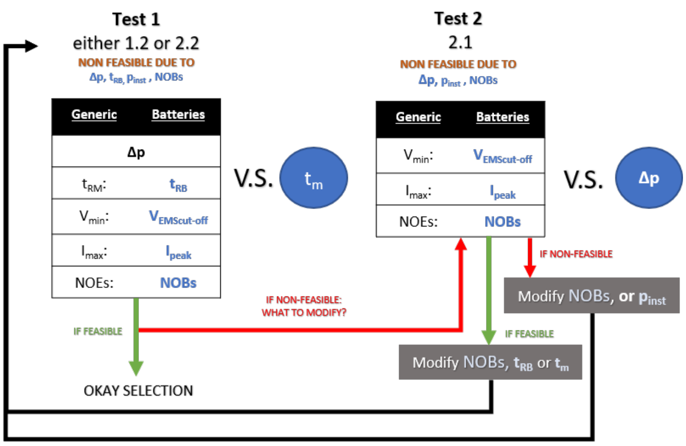


Figure 19: Operational Feasibility Check

From deduction 2 EMS control settings with smaller cut-off voltage bands, e.i., excluding higher discharge voltage drops, are favourable for higher power responses, hence, wider feasibility ranges.

In addition, it is reaffirmed how fastest response and higher number of batteries help to comply with operational feasibility.

To evaluate feasibility, the worse case scenario is maximized for I_{peak} equal to maximum peak discharge current specified for the power source to install.

3.1.4 Batteries capacity reduction per cycle

To evaluate the capacity detriment under operation it is used, for each storage element, the data extracted from open source data sheets. For batteries, the calculus is done over 3 different DOD of 50%, 80% and 100% of the nominal battery capacity, tested at 25 degrees Celsius and at a C-rate of 0.5.

To reduce computational time, and considering that, usually, the capacity detriment per cycle is a linear function for batteries analysed up to 70% SOC, function slope mean values are extracted from two different methods. The first one evaluates Q detriment per cycle each value from the discrete data sample inserted, finishing the calculus with the mean of all of them. The second one is the calculation of the slope from the first and last value of the discrete data series introduced. Both could be mathematically expressed as it follows:

$$C_v(z)[kWh/cycl] = \frac{\%_{Q_{N_{red}}}(z) - \%_{Q_{N_{red}}}(z-1)}{N_{cycles}(z) - N_{cycles}(z-1)} \times Q_N \tag{19}$$

1.
$$Q_{mrc1}[kWh/cycl] = \frac{\sum_{z=1}^{z} C_v}{z} \tag{20}$$

2.
$$Q_{mrc2}[kWh/cycl] = \frac{\%_{Q_{N_{red}}}(z) - \%_{Q_{N_{red}}}(1)}{N_{cycles}(z)} \times Q_N \tag{21}$$

Being z the the number of discrete data steps introduced.

To evaluate which one is the best approach, the accumulated error is extracted comparing the final mean value and the capacity reduction per cycle each data step registered, each method. It is expected that the first method fits better with non-linear functions input and the second one with linear ones. When the capacity reduction per cycle is given in a non-linear function the accuracy of the calculation must be re-evaluated. To evaluate method feasibility the total accumulated error over the whole data sample is calculated but for the evaluation of the expected error at the specific time during operation from this calculation, mean error from the whole data sample is accumulated each time step and applied to the optimization algorithm.

The error track of this proposed methodologies applies to:

1. **Measurement error:** The measurements come from battery data sheets under specific conditions but further deviations due to temperature or working conditions, e.g. C-rate, could change the data input, e.i., capacity reduction VS number of cycles. This is neglected for this first project scope but keeps open for study. Sensors sensibility could be also included here if required.

2. **Image to discrete data sample error (computing error):** Data sheets are commonly given in image format, then, the extraction of the discrete data from the image should be

also consider to track the error. The more accurate this extraction becomes the better the evaluation of the approximation error could be. For this scope this error is considered in the results evaluation but not analysed individually.

3. **Approximation error:** The approximation error, which could include computing error if required, is the one extracted from the calculus simplification with the slope values proposed methods, e.i. it is accurate enough to use the mean slope value calculation each function? How much is the impact in the battery pack sizing?.

To evaluate which methodology suits better to simplify the calculation two error indexes are extracted, Error Accumulated Index (EACCI) and Error Maximum Index (EMXI). EMXI is just the maximum error per cycle in kWh among the whole data sample to identify unexpected random values from the data introduced which could reflect data insertion failures or measurements noise. EACCI calculation is shown equation 23 and use to evaluate the expected accumulated calculus error from equations 20 and 21 during a specific number of cycles at the three different maximum DOD of study for different batteries models. As a test example four batteries are selected with the correspondent input data illustrated in Figure 20. The accumulated estimated error up to its assumed death (70% capacity detriment) each battery at 3 different depth of discharge is included in Table 9. The existence of *image-to-discrete data error* forces to use identifiers to detect if this random error is strongly present in the calculations (EMXI). Accumulated error values are estimated for 30 years of battery operation at a fixed DOD per cycle in Table 9, considering battery fully recharge each hour during the whole life.

$$\epsilon_{1/2}(z) = \left(C_v(z) - Q_{mrc1/2}\right)/C_v(z) \tag{22}$$

$$EACCI_{1/2}\,[kWh] = \sum_{DOD=[50,80,100]} \left(\frac{\sum \epsilon_{1/2}[kWh]}{N_{TD_{cycl_{DOD}}}} \times N_{T_{cycl}} \times \frac{\%_{cycl_{DOD}}}{100} \right) \tag{23}$$

$$EMXI\,[kWh] = max\left(max\left(\epsilon_{1/2_{DOD}}\right)\right)_{DOD=[50,80,100]} \tag{24}$$

s.t.

$\%_{cycl_{DOD}}$ = percentage of the total number of cycles operated up to specific DOD.

$N_{T_{cycl}}$ = total number of cycles required for the specific case study.

$N_{TD_{cycl_{DOD}}}$ = number of cycles up to death each DOD.

The results of the present evaluation are part of a first inner loop of the algorithm just to extract the best method depending on the percentage of cycles, from the total number of cycles, operating at the 3 different DOD defined in the structure, 50%, 80% and 100% of Q_N; the input data from the batteries data sheet in the form of Figure 20; and total number of cycles, dependent on autonomy settings.

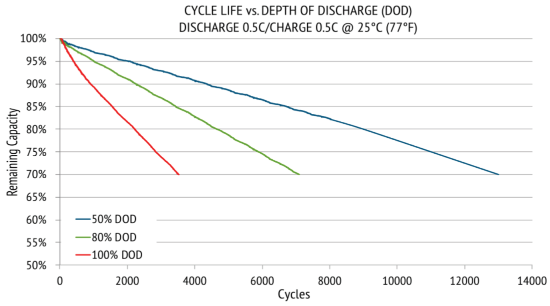


Figure 20: Capacity Reduction per Cycle. ReLion batteries data sheet [?].

Considering the input from a previous sizing loop where the 70% of the total number of cycles tested are operated up to 50 DOD, the 25% up to 80 DOD and just the 5% achieves a full discharge per cycle, Table 9 shows the resulting capacity reduction per cycle mean values and the correspondent accumulated error indexes to compare between the two presented methodologies. From these specifications all indexes indicate how the first methodology best suits with the introduced discrete data. Nevertheless, from deeper analysis, specific error calculations as smaller batteries with higher DODs values per cycle (of 80% or full discharge) could suffer from lower accuracy if Method 1 is used. In a second step of elaboration this would be further analysed but for the present scope the method selection criteria will follow the most generic analysis from Table 10.

Table 10 evaluates the presented indexes in the section for different amount of cycles with specific maximum DOD of design. No matter how much cycles each DOD value, Method 1 ends up being more accurate for the present data introduced.

Table 9: Capacity Reduction per Cycle Mean

				Total number of cycles:	**262800**				
			DOD:	**50**	**80**	**100**	**N of years:**		30
			Cycles to death:	3500	7100	13100	**Aut (h):**		1
			% cycles per DOD:	70	25	5			
Variables in [%] units		**VECTORS METHOD 1**							
		B1, Q$_N$ $= 20Ah(0.23kWh)$			**KPIs**	**B2, Q$_N$** $= 50Ah(0.58kWh)$			**KPIs**
DOD		**50**	**80**	**100**	**EACCI - EMXI**	**50**	**80**	**100**	**EACCI - EMXI**
Q_{rcm}	[kW]	0.0002	0.0005	0.0019		0.0013	0.0023	0.0049	
$Error_{acc}$ **(up to death)**	[kW]	0.1076	0.0090	0.0064	**5.7394**	0.0339	0.0079	0.0256	**1.8537**
$Error_{acc}$ **(up to death)**	[kW]	0.0245	0.0003	0.0006	**0.0245**	0.0011	0.0012	0.0053	**0.0053**
		B3, Q$_N$ $= 100Ah(1.15kWh)$			**KPIs**	**B4, Q$_N$** $= 300Ah(3.46kWh)$			**KPIs**
DOD		**50**	**80**	**100**	**EACC - EMX**	**50**	**80**	**100**	**EACC - EMX**
Q_{rcm}	[kW]	0.0012	0.0038	0.0094		0.0077	0.0138	0.0278	
$Error_{acc}$ **(up to death)**	[kW]	0.0505	0.0241	0.0352	**2.8786**	0.1848	0.1708	0.1023	**11.2933**
$Error_{max}$ **(up to death)**	[kW]	0.0010	0.0020	0.0044	**0.0044**	0.0084	0.0122	0.0253	**0.0253**
		VECTORS METHOD 2							
		B1, Q$_N$ $= 20Ah(0.23kWh)$			**KPIs**	**B2, Q$_N$** $= 50Ah(0.58kWh)$			**KPIs**
DOD		**50**	**80**	**100**	**EACCI - EMXI**	**50**	**80**	**100**	**EACCI - EMXI**
Q_{rcm}	[kW]	0.0005	0.0010	0.0019		0.0013	0.0024	0.0050	
$Error_{acc}$ **(up to death)**	[kW]	0.4730	0.0077	0.0069	**24.9334**	0.0348	0.0083	0.0264	**1.9056**
$Error_{max}$ **(up to death)**	[kW]	0.1142	0.0008	0.0006	**0.1142**	0.0011	0.0013	0.0054	**0.0054**
		B3, Q$_N$ $= 100Ah(1.15kWh)$			**KPIs**	**B4, Q$_N$** $= 300Ah(3.46kWh)$			**KPIs**
DOD		**50**	**80**	**100**	**EACC - EMX**	**50**	**80**	**100**	**EACC - EMX**
Q_{rcm}	[kW]	0.0026	0.0049	0.0098		0.0079	0.0144	0.0295	
$Error_{acc}$ **(up to death)**	[kW]	0.0718	0.0135	0.0382	**3.8995**	0.1928	0.1848	0.1222	**11.8459**
$Error_{max}$ **(up to death)**	[kW]	0.0022	0.0019	0.0052	**0.0052**	0.0090	0.0140	0.0303	**0.0303**

Table 10: EACCI & EMXI resulting values for 262800 cycles for % of them at three different DODs

Total number of cycles:						**262800**											
		DOD	50	80	100			**DOD**	50	80	100			**DOD**	50	80	100
	% cycles per	**DOD**	**20**	**20**	**60**		**% cycles per**	**DOD**	**20**	**60**	**20**		**% cycles per**	**DOD**	**30**	**70**	**0**
		B1	B2	B3	B4			B1	B2	B3	B4			B1	B2	B3	B4
METHOD 1	EACCI	1.683	0.567	0.937	4.039	METHOD 1	EACCI	1.716	0.596	1.026	4.671	METHOD 1	EACCI	2.658	0.967	1.762	8.587
	EMXI	0.025	0.005	0.004	0.025		EMXI	0.025	0.005	0.004	0.025		EMXI	0.025	0.005	0.004	0.025
METHOD 2	EACCI	7.160	0.584	1.178	4.264	METHOD 2	EACCI	7.189	0.614	1.229	4.948	METHOD 2	EACCI	10.854	0.998	1.968	9.132
	EMXI	0.114	0.005	0.005	0.030		EMXI	0.114	0.005	0.005	0.030		EMXI	0.114	0.005	0.005	0.030
		DOD	50	80	100			**DOD**	50	80	100			**DOD**	50	80	100
	% cycles per	**DOD**	**50**	**10**	**40**		**% cycles per**	**DOD**	**50**	**25**	**25**		**% cycles per**	**DOD**	**50**	**40**	**10**
		B1	B2	B3	B4			B1	B2	B3	B4			B1	B2	B3	B4
METHOD 1	EACCI	4.073	1.301	1.986	7.570	METHOD 1	EACCI	4.123	1.345	2.120	8.518	METHOD 1	EACCI	4.174	1.388	2.253	9.466
	EMXI	0.025	0.005	0.004	0.025		EMXI	0.025	0.005	0.004	0.025		EMXI	0.025	0.005	0.004	0.025
METHOD 2	EACCI	17.787	1.337	2.746	7.924	METHOD 2	EACCI	17.830	1.383	2.821	8.950	METHOD 2	EACCI	17.873	1.429	2.896	9.976
	EMXI	0.114	0.005	0.005	0.030		EMXI	0.114	0.005	0.005	0.030		EMXI	0.114	0.005	0.005	0.030
		DOD	50	80	100			**DOD**	50	80	100			**DOD**	50	80	100
	% cycles per	**DOD**	**70**	**5**	**25**		**% cycles per**	**DOD**	**70**	**10**	**20**		**% cycles per**	**DOD**	**70**	**25**	**5**
		B1	B2	B3	B4			B1	B2	B3	B4			B1	B2	B3	B4
METHOD 1	EACCI	5.672	1.796	2.700	10.029	METHOD 1	EACCI	5.689	1.810	2.745	10.345	METHOD 1	EACCI	5.739	1.854	2.879	11.293
	EMXI	0.025	0.005	0.004	0.025		EMXI	0.025	0.005	0.004	0.025		EMXI	0.025	0.005	0.004	0.025
METHOD 2	EACCI	24.877	1.844	3.799	10.478	METHOD 2	EACCI	24.891	1.860	3.824	10.820	METHOD 2	EACCI	24.933	1.906	3.899	11.846
	EMXI	0.114	0.005	0.005	0.030		EMXI	0.114	0.005	0.005	0.030		EMXI	0.114	0.005	0.005	0.030

Table 11: Expected Number Of Batteries sizing error from the computing error of the capacity reduction per cycle insertion

Batteries		**1**	**2**	**3**	**4**			**1**	**2**	**3**	**4**			**1**	**2**	**3**	**4**
Q_N	**kWh**	**0.23**	**0.58**	**1.15**	**3.46**			**0.23**	**0.58**	**1.15**	**3.46**			**0.23**	**0.58**	**1.15**	**3.46**
		DOD	50	80	100			**DOD**	50	80	100			**DOD**	50	80	100
	% cycles per	**DOD**	**20**	**20**	**60**		**% cycles per**	**DOD**	**20**	**60**	**20**		**% cycles per**	**DOD**	**30**	**70**	**0**
METHOD 1	EACCI	7.3	1.0	0.8	1.2	METHOD 1	EACCI	7.5	1.0	0.9	1.4	METHOD 1	EACCI	11.6	1.7	1.5	2.5
	EMXI	0.1	0.0	0.0	0.0		EMXI	0.1	0.0	0.0	0.0		EMXI	0.1	0.0	0.0	0.0
METHOD 2	EACCI	31.1	1.0	1.0	1.2	METHOD 2	EACCI	31.3	1.1	1.1	1.4	METHOD 2	EACCI	47.2	1.7	1.7	2.6
	EMXI	0.5	0.0	0.0	0.0		EMXI	0.5	0.0	0.0	0.0		EMXI	0.5	0.0	0.0	0.0
		DOD	50	80	100			**DOD**	50	80	100			**DOD**	50	80	100
	% cycles per	**DOD**	**50**	**10**	**40**		**% cycles per**	**DOD**	**50**	**25**	**25**		**% cycles per**	**DOD**	**50**	**40**	**10**
METHOD 1	EACCI	17.7	2.2	1.7	2.2	METHOD 1	EACCI	17.9	2.3	1.8	2.5	METHOD 1	EACCI	18.1	2.4	2.0	2.7
	EMXI	0.1	0.0	0.0	0.0		EMXI	0.1	0.0	0.0	0.0		EMXI	0.1	0.0	0.0	0.0
METHOD 2	EACCI	77.3	2.3	2.4	2.3	METHOD 2	EACCI	77.5	2.4	2.5	2.6	METHOD 2	EACCI	77.7	2.5	2.5	2.9
	EMXI	0.5	0.0	0.0	0.0		EMXI	0.5	0.0	0.0	0.0		EMXI	0.5	0.0	0.0	0.0
		DOD	50	80	100			**DOD**	50	80	100			**DOD**	50	80	100
	% cycles per	**DOD**	**70**	**5**	**25**		**% cycles per**	**DOD**	**70**	**10**	**20**		**% cycles per**	**DOD**	**70**	**25**	**5**
METHOD 1	EACCI	24.7	3.1	2.3	2.9	METHOD 1	EACCI	24.7	3.1	2.4	3.0	METHOD 1	EACCI	25.0	3.2	2.5	3.3
	EMXI	0.1	0.0	0.0	0.0		EMXI	0.1	0.0	0.0	0.0		EMXI	0.1	0.0	0.0	0.0
METHOD 2	EACCI	108.2	3.2	3.3	3.0	METHOD 2	EACCI	108.2	3.2	3.3	3.1	METHOD 2	EACCI	108.4	3.3	3.4	3.4
	EMXI	0.5	0.0	0.0	0.0		EMXI	0.5	0.0	0.0	0.0		EMXI	0.5	0.0	0.0	0.0

Then, Table 11 translates these indexes into expected number of batteries sizing error inside the battery pack each battery size included in the evaluation for the different maximum DOD presented, extracted from the evaluation concerning capacity detriment per cycle. Definitely, the error is maximum for smaller batteries data insertion for both methods. The data from the table represents the equivalent number of batteries required to cover the expected error among this 30 years proposed with no re-charge needs, which makes the error result not a strong warning even for the worse cases. If these batteries are considered recharged each cycle, as the rest of the battery pack in this algorithm presentation, the error per cycle is minimum following the resulting values in Table 11.

For algorithm insertion it must be taken into account that the present error simplification is dependent on the total number of cycles carried out by the battery and the percentage of them at each considered DOD. In further studies a dynamic measure of it could be done improving accuracy by considering also the dynamic error among the capacity reduction curve inserted dependent on the instantaneous cycle number. At the present scope the method is first evaluated and selected, Method 1 in this case, then the mean calculation from method 1 of the capacity reduction per cycle is applied considering an acceptable error maximization for the present evaluation among 40 years of operation.

3.2 Algorithm structure

3.2.1 Assumptions

1. A battery module connected by several cells in parallel could be considered as a single cell with high capacity. Hence the SOC could be estimated like a single cell (due to the self-balancing characteristic of the parallel connection), [20].
2. Minimum DOD of 50 to consider battery capacity detriment which influences battery life.
3. Battery replacement each 30% detriment of the nominal capacity by design.
4. By now just batteries are considered as alternative of diesel engines in the evaluation. Alternative fuels are not included for this project scope.
5. If the instantaneous power-speed response of the battery bank by design complies with the ship load motions requirements the system is considered controllable.
6. $t_{RS} = t_{RC}$ in Figure 27. To reduce computational time, the maximum time the battery pack uses to reduce the power response is assumed equal to the peak discharge time. For maximum error estimation the accuracy of this assumption is enough for the present scope but a target for further study. This parameter is directly linked with the Battery Management System response time and the battery pack chemical resistance for a given input of power set points.
7. To evaluate capacity detriment per cycle a C-rate of 0.5 is considered under the lack of data for the nominal capacity detriment under any other charge/discharge rates inside the open source data sheets for batteries. This point is open to include a proper C-rate estimation, dependency variable in the capacity reduction per cycle calculus and its correspondent error, to process further missing data inclusion.

To main environments for development support the algorithm structure:

- **Feasibility Environment:**

  All constraints come from the data input environment to elaborate a structure to test the feasibility of the solution each inserted combination of elements. This structure is organized as binary data to first get rid of the non-feasible options before going through the optimization environment to reduce computational time. Considering the increasing number of available technologies for installation in the market a powerful first filter linking solutions with potential application scenarios is required, e.g. batteries for cold weather conditions, heavy duty diesel engines or high percentage of the time within idle conditions. If the filtering is well defined the computational cost for evaluating all existing solutions could already include experts considerations and strongly reduce the computational effort still keeping the whole market perspective. The presented binary environment at this scope confronts the following elements for exclusion:

  1. **Between components (BC):** Many components considered in a potential solution are not able to be installed together, neither all fuel types matches with all machinery available in the market. These evaluation could required from expertise to ensure compatibility levels and also needs for updates among time with new systems solutions. At the present scope a first analysis form an overall market perspective in Section 2.2 is procured and it will be implemented in future work when new components are inserted

in the algorithm as fuel cells, super capacitors or alternative fuels. The present matrix, as a constraint, is able not just to identify the feasible solutions but also to fix desirable machinery combos by the engineers or shipowners. Table 12 shows how to elaborate the constraints matrix between components from non compatible solutions to desired combos (more restrictive).

Table 12: Constraints Matrix Between Components

Machinery (BC_m)	Engine	Gensets	Battery	Fuel Cell	Supercap	Dual Fuel Engine	**CONSTRAINED MODES**
Engine	1	0	1	1	1	0	**M1**
Gensets	0	1	1	1	1	0	**M2**
Battery	1	1	1	1	1	1	**M3**
Fuel Cell	1	1	1	1	1	1	**M4**
Supercap	1	1	1	1	1	1	**M5**
Dual Fuel Engine	0	0	1	1	1	1	**M6**
Machinery (BC_{md})	Engine	Gensets	Battery	Fuel Cell	Supercap	Dual Fuel Engine	**DESIRED MODES**
Engine	0	0	0	0	0	0	**M1**
Gensets	0	1	1	0	0	0	**M2**
Battery	0	1	1	0	0	0	**M3**
Fuel Cell	0	0	0	0	0	0	**M4**
Supercap	0	0	0	0	0	0	**M5**
Dual Fuel Engine	0	0	0	0	0	0	**M6**

Then the final Constraint Matrix Between Components should be the Hadamard product of both two matrices:

$$BC = BC_m \circ BC_{md} \tag{25}$$

2. **Project specifications VS components application (PS VS CA):** Different brands includes clear recommendations for when to install, for instance, its engines at different system design solutions or specific environments of operation, e.g. operating temperature ranges. Some of these considerations are analysed in Section 2.2 and applied to the algorithm. One of them is batteries under low temperature working conditions for the present case study and

3. **Expected operation profile (Load Profile) VS components type (LP VS CT):** Same restrictions could be applied by confronting the ship power profile to every component type. Some manufacturers recommend to use specific type of machines considering the percentage of operational profile under idle conditions, peak loads or specific continuous loading to ensure longer components life and higher safety levels.

4. **Ship design constraints (SDC):** The overall ship design at the preliminary design phase is mainly connected to the power plant design via ship design constraints. They include weight, space and autonomy and they are built from as much contributions and conditions as the design requires. For instance, the space constraint considers for batteries two orientations for the battery pack installation, or the weight is limited form the most restrictive input either external stability requirements or maximum service speed detriment due to weight increment limiting factor. The relational data table will be the key element to define functions as for the exemplified relations.

5. **System operation constraints (SOPC):** This part of the feasibility environment is one intended for the machinery and system response analysis. At the beginning the analysis considers feasible the operation up to the limits defined by the manufacturer but future work is expected to include tightened control limits from detailed modeling of the optimum solutions as it has been already mentioned. The operational feasibility is first approached by the conditions extracted from the energy measurements data processing inside Section 3.1.3 for batteries and extended for Gensets by the following formulas inclusion:

The above mentioned environments number 2 and 3 will be located in an application filter previous feasibility evaluation, which development is first approached in Section 3.1, where the market environment is tightened from its first window of solutions.

Table 13: Feasibility matrices insertion from the overall perspective and the present scope

MATRICES INSERTION	**Present Scope**			**Future Work**						
Mode/Feasiblity Constraint	**FEM**	**FFHM**	**FFM**	**FEM**	**FFHM**	**FFM**	**AFM**	**AFHM**	**GTM**	**GTHM**
BC				X	X	X	X	X	X	X
PS VS CA	X			X	X	X	X	X	X	X
LP VS CT			X	X	X	X	X	X	X	X
SDC	X	X	X	X	X	X	X	X	X	X
SOPC	X	X	X	X	X	X	X	X	X	X

Table 13 illustrates the development process of the feasibility environment from the overall perspective. For the present scope there is no compatibility matrices inserted between components, considering the ones evaluated inside the scope compatible with each other, e.i. diesel engines and batteries combos from Figure 9. The project environment is taken into account selecting batteries design for low temperature operation but not further considered in diesel engines type selection. On the other hand, the load profile is confronted with diesel engines selection as a first filter from the fossil fuels mode but not filtered in FEM or FFHM. Constraints environments from ship design variables and operational feasibility are both included for this scope. Future work will perform the analysis of the feasibility environment among all them interconnected feasibility environments. The final holding structure must follow the mathematical notation in equation 26.

$$(FE_T)_{ijkp} = (BC \times CM)_i = \left(\sum_{n=1}^{n} BC_n \times CM_n \right)_i \tag{26}$$

$$(FE_T)_{i^*j^*k^*p^*} = (FE_T)_{ijkp} \tag{27}$$

Being:

$FE_T \in 0, 1$ = Feasibility Environment Matrix, getting rid of the non-feasible solutions.

$BC = [BC_1 \ (...) \ BC_n], BC_n \in \{0, 1\}$ = Between Components Matrix.

$CM_{ijkp} = [CM_1 \ (...) \ CM_n]^T, CM_n \in \{0, 1\}$ = Constraints Matrix.

$CM_{ijkp_n} = mkt_{ij_nk_np_n} \times sdc_{ij_nk_n} \times sopc_{ij_nk_n}$

$mkt_{ij_nk_np_n} = 1 \in MKT$ = 4D array, market input sizing array.

$sdc_{ij_nk_n} \in SDC \in \{0, 1\}$ = 3D array (into 4D for computation), ship design constraints.

$sopc_{ij_nk_n} \in SOPC \in \{0, 1\}$ = 3D array (into 4D for computation), system operation constraints.

$ft_{j_nk_n} \in FT \in \{0, 1\}$ = 2D array (into 4D for computation), fuel type VS machinery.

$n \in \mathbb{Z}-+$ = number of different components for energy production, e.g. batteries, fuel cells or Gensets.

i = load profile measurement step ∈ I. For i^* non feasible solutions are disregarded.

j = machinery type ∈ J of element group type n. For j^* non feasible solutions are disregarded.

k = loading range ∈ K of element group type n. For k^* non feasible solutions are disregarded.

p = fuel type ∈ P of element group type n. For p^* non feasible solutions are disregarded.

- **Multi-Objective Optimization Environment:**

  The optimization environment is defined by a multi-objective constrained linear optimization where to minimize emissions and costs and maximize safety. It is subjected to costs limits defined by any of the interested parties, emissions limitations implemented from rules and regulations or further restricted by clients wishes, and minimum safety levels limitations from rules. As a first step of development, simple weighted method is presented as a holding structure in equation 28. Nevertheless, this is not the expected final solution, aiming for a tuned multi-objective optimization method which well suits for the final data analysed.

$$minimize\, F(x) = \sum_{m=1}^{M} w_m f_{op_m}(x)_{i^*j^*k^*p^*} \quad \forall M = [COST, EMISSIONS, SAFETY]. \tag{28}$$

  Subjected to:

$$g_l(x) \geq 0,\ l = 1, 2, ..., L \tag{29}$$

$$h_o(x) = 0,\ l = 1, 2, ..., O \tag{30}$$

  - **Cost function,** f_{op_1}**:** The cost function is elaborated as the summary of all boxes presented in Figure 21. The present function takes a first shape with the case study included for analysis in the document and will be re-elaborated each new case study up to conclude with a generic one.

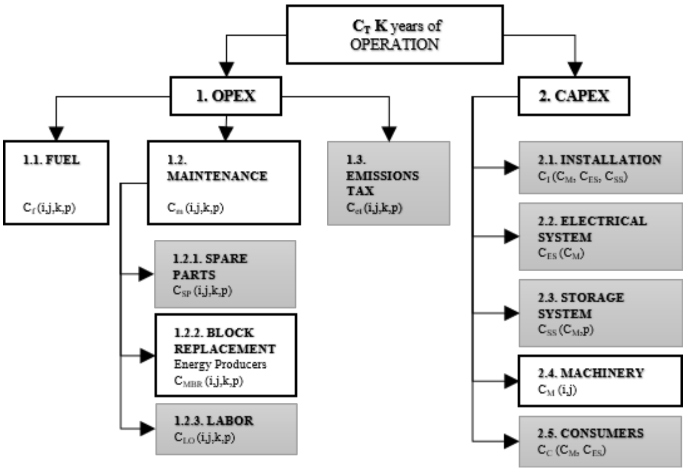


Figure 21: Total Costs Function

  Optimized solution in terms of costs:

$$f_{op_1} = c_{TC_{j^*k^*p^*}} = min\left(\sum_{i \in I} c_{TC_{i^*j^*k^*p^*}}\right) \tag{31}$$

  - **Emissions function:** CO_x, SO_x and NO_x must be minimize following structures for emissions calculation included in Appendix A but inserting different conversion factors for all emissions type considered.
  - **Safety function:** It is not targeted yet in the present project but a conceptual evaluation linking rules and regulations in done with the case study analyzed.

FIRST SIMPLIFIED ASSESSMENT:

Under a first simplification of the algorithm just Gensets and batteries, as energy storage components in the system are assessed, combinations 9, 10 and 17 from Figure 9.

From the feasibility environment:

The application filter between components is just used to get rid of the combinations out of the analysis but both Gensets and batteries can work together, $BC_{md} = BC$. From PS VS CA filtering, batteries are selected with Lithium Ion chemistry, low temperature working conditions and capacity ranges from 20 to 300 Ah; and Gensets for Diesel-Electric applications, unlimited running hours, speed of 750 rpm and two of them with the same MCR as the currrenly stalled ones and two additional models, one smaller and the other largen then all of the rest. SDC considered are autonomy, weight and space which dependencies to packages insertion are included in Table 14. SOPC considered are maximum instantaneous speed of response and maximum power drop which dependencies to packages insertion are included in Table 14. In addition, overloading is also inserted as operational constraint for Gensets.

Table 14: Feasibility Environment first simplification

	Constraints	Units	Intervening parameters	Options	Mode	Assumptions	Intervening packages
				Ship Design Feasibility			
			$E_{d_{acum}}$	Fix	FEM	Intial SoC = 100%;	Ship type (LP)
1	Autonomy	years	$t_{autonomy}$	Fix	FEM	Full re-charge at port or Offshore re-charge services	Project Nature (PSPCs)
			$E_{d_{acum}}$	Variable	FFHM	Gensets optimum	Ship type (LP)
			$t_{autonomy}$	Variable	FFHM	recharge dependency	internal variables
2	Weight	kg	max. Installation Weight	Fix	FEM/FFHM	More restrictive constraint	Project Nature (min(PSPCs,CW))
				Max. Speed detriment	FEM/FFHM	selection diff. from 0	Relational Data Table
		m	machinery room Length	Fix	FEM/FFHM		Project Nature (PSPCs)
		m	machinery room Width	Fix	FEM/FFHM		Project Nature (PSPCs)
		m	machinery room Height	Fix	FEM/FFHM		Project Nature (PSPCs)
3	Space	m	min. Length margin	Fix	FEM/FFHM	Safety + Maintenance space margins	Project Nature (PSPCs)
		m	min. Width margin	Fix	FEM/FFHM		Project Nature (PSPCs)
		m	min. Height margin	Fix	FEM/FFHM		Project Nature (PSPCs)
			B. orientation (St-Bw;Pt-Sb)	Fix	FEM		Project Nature (PSPCs)
			% B	Fix	FFHM	% Gensets = (1 - % Batteries)	Project Nature (PSPCs)
				Operational Feasibility 1			
4	Max. Inst. Speed	ΔkW/Δt	$E_{d_{acum}}$	Fix	FEM/FFHM	From E_{accum} error estimation	Ship type (LP)
		t	$t_{R_{machinery}}$	Fix	FEM/FFHM		Machinery Combos (MCO)
				Operational Feasibility 2			
5	Max. Power drop	ΔkW	$power_{drop}$	Fix	FEM/FFHM	From direct LP inst measurements	Ship type (LP)
		t	t_m	Fix	FEM/FFHM		Ship type (LP)

From equation 26:

$$(FE_T)_{ijkp} = [BC \times CM_{ijkp}] \tag{32}$$

$$BC = \begin{bmatrix} 1 & 1 \end{bmatrix} \times \begin{bmatrix} \mathbf{CM_B}_{ijkp} & \mathbf{CM_G}_{ijkp} \end{bmatrix}^T \tag{33}$$

From the above written equations i^*, j^*, k^*, p^*, are extracted as the feasible options for being inserted into the optimization environment.

From the optimization environment:

The cost function is first scoped from fuel type, and machinery blocks replacement (components death estimation), inside the OPEX evaluation and machinery costs from CAPEX evaluation. Results discussion and conclusions take into account the present simplification for a proper interpretation. Hence, the results value will be lead by a comparative expression between different potential power plant sizing solutions with a solid output structure for inserting deeper analysis with the rest of boxes from the cost function in Figure 21. A first estimation of CO_x, SO_x and NO_x emissions is also included in the following section with a similar structure as the one presented for EEDI calculations in Appendix A. From equation 28:

$$min\left(F(x)\right) = min\left(f_{op_{COST}}\right) \tag{34}$$

4 Case Study

Blue Queen (Kasteelborg), Figure 22, is studied for a retrofit project. A ship originally delivered as a medium-sized platform supply vessel of the PX121 design, built by Ulstein Verft A.S. and operated by Wagenborg Offshore, converted to a Walk-to-Work emergency response and rescue vessel, W2W ERRV, for the inspection and maintenance of unmanned platforms, [35]. Kastelborg is currently sailing under the flag of Netherlands.

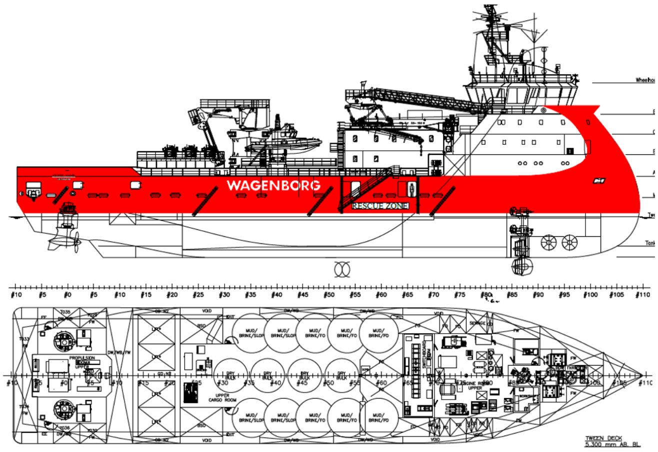


Figure 22: Kasteelborg conceptual drawings. *Source: https://www.wagenborg.com*

The vessel is classified within DNV rules and regulations with the notation in Table 15 where the last column and blue cells reefers to relevant literature from DNV for the power plant evaluation and rules compliance.

Table 15: KASTEELBORG current class notation from DNV.

1	DNV 1A1			
2	Offshore Service Vessel, Supply			*Mandatory: no* *Design requirements:* *Pt.5 Ch.9 Pt.6 Ch.5 Sec.15* *FIS survey requirements:* *Pt.7 Ch.1 Sec.2, Pt.7 Ch.1 Sec.3, Pt.7 Ch.1 Sec.4 and Pt.7 Ch.1 Sec.6 [32]*
3	SF		Compliance with requirements to damage stability	Mandatory: no Design requirements: Pt.6 Ch.5 Sec.6 FIS survey requirements: NA
4	E0			*Mandatory: no* *Design requirements: Pt.6 Ch.2 Sec.2* *FIS survey requirements: Pt.7 Ch.1 Sec.6*
5	DYNPOS-AUTR	Dynamic positioning system with redundancy in technical design. Provides higher availability and robustness compared to DPS(2).	Includes redundant DP control system, single joystick control system and manual levers control backup.	*Mandatory: no* *Design requirements: Pt.6 Ch.3 Sec.1 and Pt.6 Ch.3 Sec.2* *FIS survey requirements: Pt.7 Ch.1 Sec.6*
6	CLEAN DESIGN		Arrangements for controlling and limiting operational emissions and discharges.	*Mandatory: no* *Design requirements: Pt.6 Ch.7 Sec.2* *FIS survey requirements: DNVGL-RU HSLC Pt.7 Ch.1 Sec.6*
7	COMF-V(3)C(3)	**C-crn: Vessels designed for enhanced comfort by improved indoor climate. crn denotes comfort rating number.**	**V-crn: Vessels designed for enhanced comfort by reducing noise and vibration. crn denotes comfort rating number.**	*Mandatory: no* *Design requirements: Pt.6 Ch.8 Sec.1* *FIS survey requirements: NA*
8	LFL*	Designed for carriage of liquid with flashpoint lower than 43°C	Mandatory for vessels intended for transportation of liquids with a flashpoint below 60°C in bulk to and from offshore installations except ship types Tanker for Oil and Tanker for chemicals.	*Design requirements: Pt.6 Ch.5 Sec.9* *FIS survey requirements:* *Pt.7 Ch.1 Sec.2, Pt.7 Ch.1 Sec.3 and Pt.7 Ch.1 Sec.4*
9	NAUT-OSV(A)		Requirements within bridge design, bridge instrumentation, and workstation arrangements. Vessels with NAUT will comply with SOLAS V/15 and IMO MSC/Circ.982. Basic requirements.	**Mandatory: no** **Design requirements: Pt.6 Ch.3** **FIS survey requirements: Pt.7 Ch.1 Sec.6**
10	DK(+)	Strengthened	Weather deck strengthened for heavy cargo	*Pt.6 Ch.1 Sec.2*
11	HL(2.8)		Tanks or holds strengthened for heavy liquid of max. = 2,8 t/m3	Mandatory: no Design requirements: Pt.6 Ch.1 Sec.3 FIS survey requirements: NA
12	ICE-C		Vessels intended for navigation in light ice conditions.	*Mandatory: no* *Design requirements: Pt.6 Ch.6 Sec.1 and Pt.6 Ch.6 Sec.2* *FIS survey requirements: NA*
13	OILREC	Recovered oil reception and transportation.	All ships except Tanker for Oil.	*Mandatory: no* *Design requirements: Pt.6 Ch.5 Sec.11* *FIS survey requirements: Pt.7 Ch.1 Sec.2 and Pt.7 Ch.1 Sec.4*

Table 16 presents the vessel specifications, including the power and propulsion systems currently installed on board. The purpose of Emergency Response and Rescue Vessels (ERRV), as Kasteelborg is defined since 2017 (2018 into service), is to attend offshore installations. They should combine good manoeuvrability, enhanced survivor reception and medical after-care facilities, updated navigational/communications equipment and rescue craft capable of operating severe weather, [3]. These requirements meant to have enough response capabilities from power and propulsion systems to ensure that maneuverability under bad weather conditions translated into high margins at the time the power plant sizing is done.

Table 16: KASTEELBORG Project Specifications

Main Dimensions		
LOA	83.4	m
L_{pp}	76.5	m
Beam	18	m
Depth to main deck	8	m
Max. Draught	6.69	m
Design draught	6	m
Power System		
Diesel-electric power and propulsion plant	MSB: 690V (SB: 440V & 230V)	
Dieselmotor, Caterpillar 3516TAC x 2	MCR 2350 bkW	at 1800 rpm
Dieselmotor, Caterpillar CAT C32 x 2	MCR 994 bkW	at 1800 rpm
Generator AVK DSG 86 M1/4W x 2	2250ekW ved pf 0.9	
Generator AVK DSG 62 L2/4W x 2	940ekW ved pf 0.9	
Emergency Power System		
Diesel Engine Motor Scania DI12 x 1	62M -260kW	
Generator Stamford HCM424D x 1	200ekW ved pf 0,8	
Propulsion System		
Propulsion Propeller x 2	RRM AZP	100CP - 2200kW
Tunel Thruster x 2	RRM TT	2000DP CP - 880kW
Azimut Thruster x 1	RRM UL1201	FP - 880kW

The present power plant design is analysed via power measurements evaluation from the currently installed Gensets output. Table 17 represents the percentage among the total running hours each Genset working at the specified loading. The 55% of the time Gensets are running at low loading conditions (≤22% of MCR), 19% of the total running hours are performed at loadings between LLO and 60%, just 8% within loading rages of 60%-90%. One of the Gensets is clearly acting as a swinging machine, absorbing, the 74% of the time, currents back flows of low power values. As it is shown in Figure 23 around 430 MWh are absorbed by the swinging machine, Genset 1 in the figure, and lost from the total energy production in 44 days of load profile registered and analysed in Section 3.1.

Table 17: Gensets loading of the currently installed Generating Sets

LLO for MDF **22** % P_{rated}

Ranges	**OPTIMAL**		**OVERLOADED**		**UNDERLOADED**		**OVERLOADED**		**UNDERLOADED**		**UNDERLOADED**	
			% of MCR									
	60%-80%		**>90%**		**<=LLO**		**80%-90%**		**LLO-60%**		**Reversed Power**	
	[h]	% of total running h	[h]	% of total running h	[h]	% of total running h	[h]	% of total running h	[h]	% of total running h	[h]	% of total running h
G1	96.90	**10%**	0.03	**0.002 %**	120.22	**11.38%**	8.98	**0.85%**	39.98	**3.79%**	789.86	**74.80%**
G2	71.78	**7%**	0.12	**0.012 %**	640.49	**60.65%**	3.91	**0.37%**	339.66	**32.17%**	0.00	**0.00%**
G3	37.34	**4%**	0.10	**0.009 %**	632.90	**59.94%**	27.18	**2.57%**	357.78	**33.88%**	0.67	**0.06%**
G4	80.85	**8%**	0.06	**0.006 %**	909.14	**86.10%**	1.14	**0.11%**	64.78	**6.13%**	0.00	**0.00%**
TOTAL	286.87	**7%**	0.31	**0.01%**	2302.75	**55%**	41.22	**1%**	802.20	**19%**	790.53	**18.72%**
			DOWN		UP		DOWN		UP		REUSE	
			HIGHT INFLUENCE, LOWER QUANTITY				LOW INFLUENCE, HIGHER QUANTITY					

The presented environment leads into some points of analysis and potential improvement:

- If the installation remains as it is, maintenance of Genset 1 should be planed carefully to avoid unexpected risks.

- Considering the nature of the load profile registered a battery pack inclusion for peak saving could apparently be a proper solution to reduce Gensets sizing. The safety margins due to the operations nature of the present vessel requires from high power margins by design, hence, if a battery pack could ensure to cover unexpected loads due to abnormal or severe weather conditions, the size margins by design of the Gensets could be also reduced.

- Following the previous statement, a proper Energy Management Strategy on board must be adopted and its approach must be included inside the design prospects to optimize the final retrofit design.

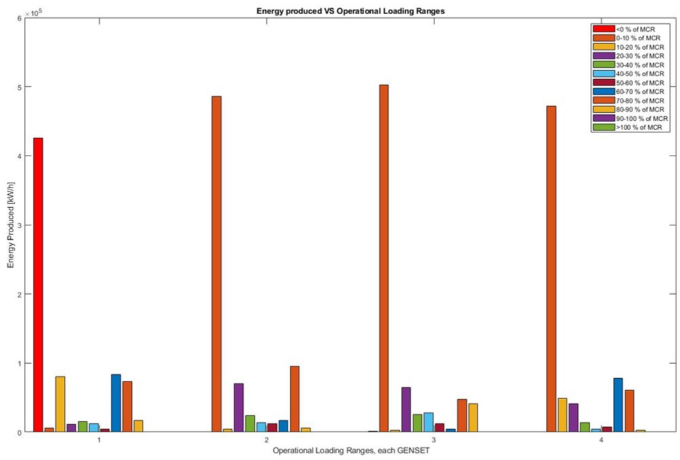


Figure 23: Energy Release [kWh] per Genset in 12 different loading slots - Current Installation

Under the present analysis the proposed algorithm is used for the evaluation of three different scenarios combining Diesel Generating Sets and batteries extracting then results for FEM, FFHM and FFM, each of them with the correspondent and already mentioned cost function simplification and further emissions output evaluation. The rest of boxes for evaluation will be included in future work.

Raw data input from machinery is considered by now in a proposed structure after a first brands extraction exposed in Figure 24 and more detailed in Appendix B. Table 18 includes the first constraints selection for the power plant design environment to test the algorithm.

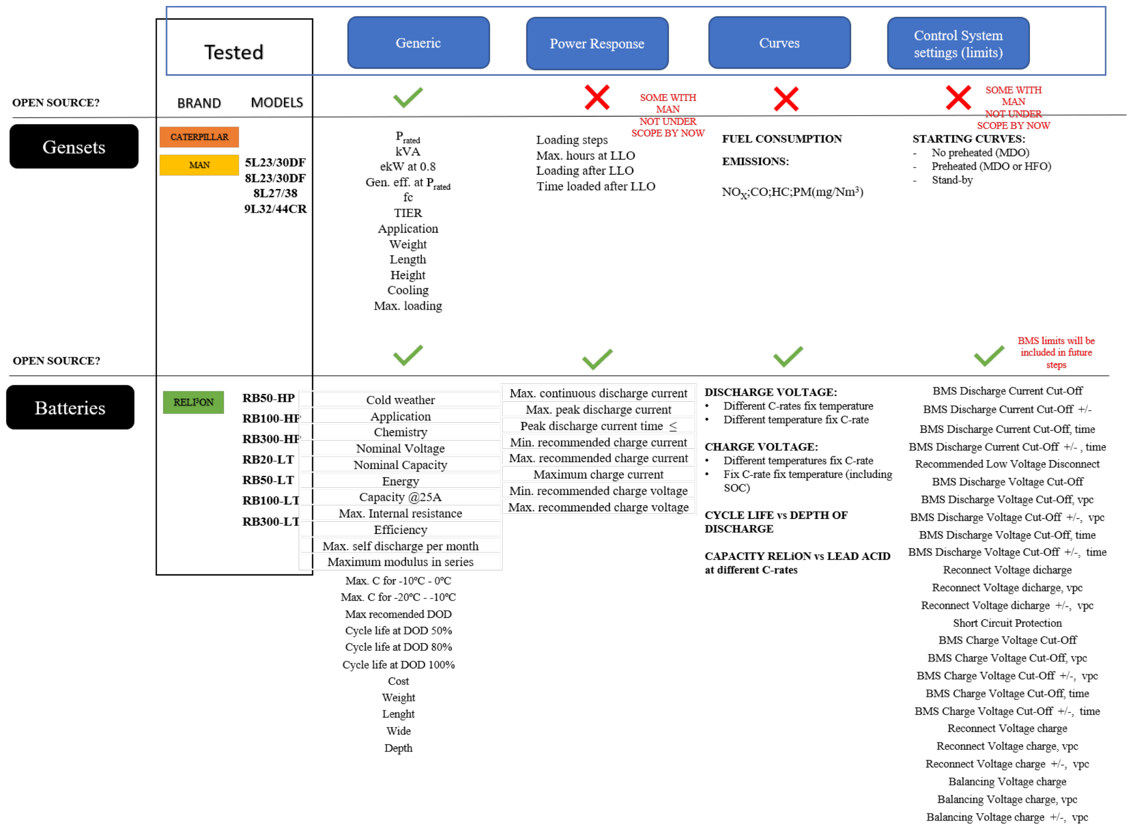


Figure 24: Machinery Input Data

Table 18: Project Specifications FEM

			Data in Accuracy
Minimum temp. working condition	-20	C^o	low
Min. autonomy (time)	**3600**	**s**	low
Min. max. design speed	15	kn	high
Machinery Room Length	25.02	m	low
Machinery Room Width	12.6	m	low
Machinery Room Depth	2.676	m	low
L "safety and add" installations marging	0.4		low
W "safety and add" installations marging	0.2		low
D "safety and add" installations marging	0.2		low
Max. weight expected for machinery installation	500000	kg	
BAT_Lithium-Ion distribution	**1**	**1/2**	
Gensets distribution	**1**	**1/2**	
Total Installed power	7256.34	kW	

4.0.1 Full Electric Mode, FEM

The evaluation starts with a Full Electric Mode analysis where the autonomy constraint plays the main role within both environments, feasibility and costs optimization. Considering a battery pack sizing problem, space and weight available to cover the energy demand from the system for a specific autonomy is one of the critical aspects for design considering batteries as elements with less energy volumetric density than fossil fuel power sources. Power density could be also critical at specific points of operation but usually batteries cover a wide range of speeds for response. They are the instantaneous and accumulated energy demands the commonly critical aspects of batteries sizing inside the system. Additionally, the electrical system, including energy transmission and protection relays are affected and reformulated for an optimum result. Hence safety is altered by risks of explosion, leakage, or system instabilities if a proper electrical system design is not considered and the best suited battery type is not selected.

With a thoughtful selection on the battery type, guided by the literature review in 2.2 the first battery chemistry included for analysis is the Lithium Ion one, from $RELI^3ON$ marine batteries. Data inserted is included in Appendix B.

Every new project follows the structure for analysis exemplify in figure Figure 25 for FEM, implementing new generic variables if required to improve the accuracy of the calculation. When inserting curves, either mean values method form Section 3.1.4 or functions curve fitting process from Section 3.1.2 are used to reduce computational time without loosing accuracy of the final evaluation. The first constraint linking the project design is weight, which increment is limited by the maximum speed of design detriment, function dependent on the installed power and evaluated in Section 3.1.2, processing data from existing ships.

The autonomy is first inserted in the operational profile to evaluate the rest of feasibility environments under its consideration. The selected variable to ensure for enough power response from the system under specific autonomy conditions is the Number of Batteries (NOBs) conforming the battery pack selection. Either weight or space constraints are externally formulated considering existing installation shaping margins or client wishes for the new solution and can be further detailed in future steps always ending up with the most restrictive constraint to be used for the final sizing, e.g. maximum % of the total LOA used for energy producers installation or its orientation, bow-stern or port starboard.

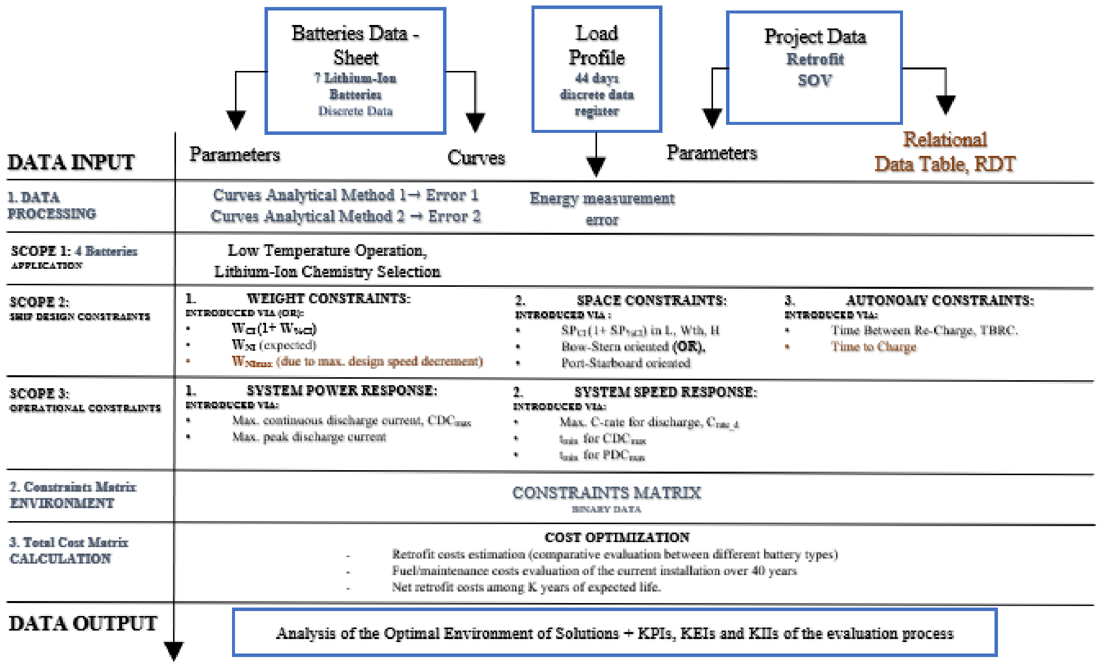


Figure 25: FEM, OSV Case Study Design Algorithm Structure

Then, from equation 32, CM_B is calculated as the Hadamard product of weight, space and operation constraint 3D (i,j,k) matrices:

$$CM_B = CM_{SP} \circ CM_{WT} \circ CM_{OP} \tag{35}$$

One side, the maximum number of batteries each size is calculated for the specified available ship space and weight, after each constraint elaboration.

On the other side, NOBs in the three mentioned dimensions are estimated to fulfill with the inserted load requirements in a first loop:

$$\text{NOBs}_{L1}(i,j,k) = \frac{E_{aut_{accum}}(i)}{(DOD_{max}(k) \times Q_N(j)) - SD(j,time) - (Q_{mrc1_{acc}}(i,j,k) + \epsilon_{mrc1_{acc}}(i,j,k))} \quad (36)$$

Where:

$E_{aut_{accum}}$: Energy demand among time each specified autonomy slot, illustrated in Figure 26 for this first run.

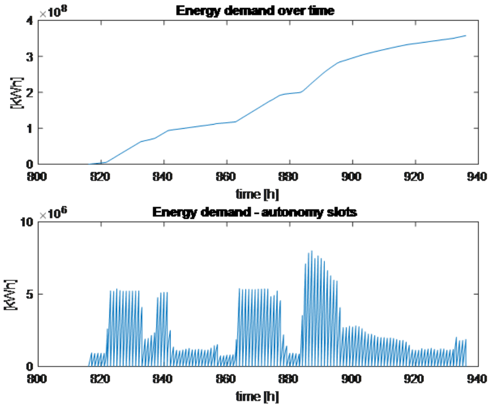


Figure 26: Energy demand

DOD_{max}: maximum depth of discharge expected from the batteries each cycle.

Q_N: nominal capacity of the batteries.

SD: self discharge of the batteries.

$Q_{mrc1_{acc}}$: capacity reduction per cycle mean calculation from method 1, Section 3.1.4, accumulated for the number of performed cycles.

$\epsilon_{mrc1_{acc}}$: error from capacity reduction per cycle mean calculation from method 1, Section 3.1.4, accumulated for the number of performed cycles.

From this first loop some comments must be presented. A battery pack conformed with more than one type of battery, or batteries from different sizes, is not under consideration. In addition to insert the energy error an inner loop dependent on NOBs is required, hence, and considering with this method the energy requirement maximized, the energy error which would optimize the result is used and safety design margin open for further evaluation in future steps for higher accuracy results. Batteries size is then fixed for an expected maximum DOD per cycle with a design margin dependent on the energy measurement expected error which dependencies are under analysis in Section 3.1.3. Figure 27 illustrates the maximum expected error, meaning potential energy demand reduction, among each autonomy slot. The maximum energy measurement expected error per autonomy slot is of 131,232×10^4 kWh or the 0.016 % the total energy demand that slot, the one considered **design safety margin in the algorithm**, measured for the smallest batteries at a maximum DOD for design of 50%.

To adjust costs in the first loop for optimization, instead of inserting an inner loop, the calculated

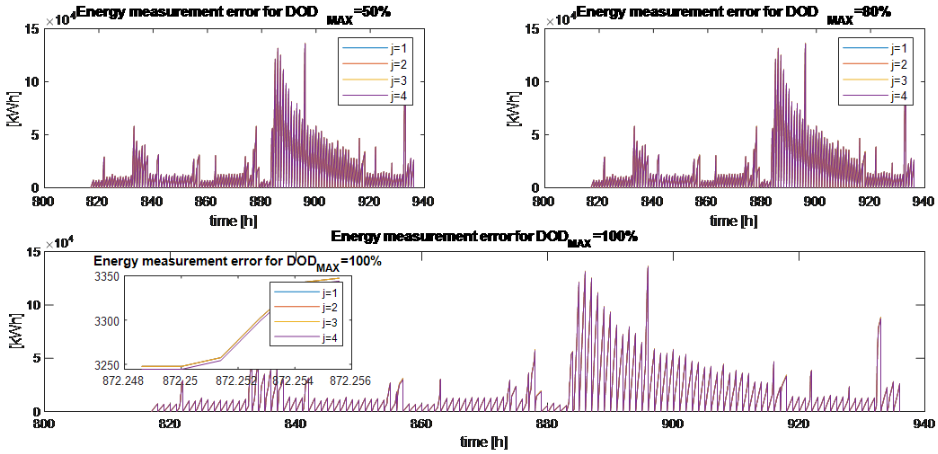


Figure 27: Energy measurement error

energy measurement error is translated into NOBs for being inserted into the cost function:

$$\epsilon_{NOBs_{L1}}(i,j,k) = \frac{\mathbf{E_{derror}(i)}}{(DOD_{max}(k) \times Q_N(j)) - SD(j,time) - (Q_{mrc1_{acc}}(i,j,k) + \epsilon_{mrc1_{acc}}(i,j,k))} \tag{37}$$

The code for the first loop is included in the Appendices Section A.1.

Then, from the simplified optimization environment it is $f_{op_{COST}}$ the function to calculate from the feasible combinations and for the blocks selection from Figure 21 for K years of ship operation.

$$f_{op_{COST}}(i,j,k) = OPEX + CAPEX \tag{38}$$

$$OPEX(i,j,k) = C_f(i,j,k) + C_{MBR}(i,j,k) \tag{39}$$

$$CAPEX(i,j,k) = C_M(i,j,k) \tag{40}$$

Being:

$$C_f(i,j,k) = E(i) \times f_c(p) \times \frac{K \times 24 \times 365}{t(n) - t(1)} \tag{41}$$

$$C_{MBR}(i,j,k) = \frac{\mathbf{NOB} \times C_B \times (Q_{mrc1_{accum}} + \epsilon_1) \times [t(n) - t(1)] \times K}{\left[1 - \frac{\%_{Bat_{depth}}}{100}\right] \times \sum t_{aut} == t_m \times 3600 \times 24 \times 365} \tag{42}$$

$$C_M(i,j,k) = \mathbf{NOB} \times C_B; \tag{43}$$

Being C_B the batteries costs and f_s specific fuel costs, e.i. electricity costs from batteries re-charge and n is the total number of load profile measurements inserted. $\%_{Bat_{depth}}$ is the percentage of the nominal capacity at which the battery is required for replacement (depth of the battery). It is noticeable how the final result is dependent on NOBs proper calculation.

For an accurate cost calculation a code re-shape must be done, not just inserting inside the loop the energy measurement error but also considering a dynamic expected DOD at which some batteries are going to perform in different autonomy slots, far from the maximum DOD of design. This new adjustment directly impacts on maintenance costs, reducing the battery detriment per cycle considering DODs lower than 50%, hence, assuming not considerable detriments from the nominal capacity.

The re-adjustment concept is explained from Figure 28. For a better understanding the maximum number of batteries solution per energy autonomy slot is called here $NOB_{max}/cycle$, hence, NOBs solutions between $max(NOB_{max}/cycle)$ and $min(NOB_{max}/cycle)$ needs from an inner loop where to recalculate costs considering an instantaneous DOD among the load profile:

$$DOD_{dyn}(i^*, j, k) = \frac{E_{aut_{acc}}(i^*) + NOBs(i, j, k) \times (Q_{mrc1_{accum}}(i^*, j, k) + \epsilon_{acc} + SD(j, time))}{NOBs(i, j, k) \times Q_N(j)} \tag{44}$$

Where i^* represents the inner loop variable for re-adjustment. An equivalent floating variable $NOBs(i^*, j, k)$ is then used to calculate the final costs function.

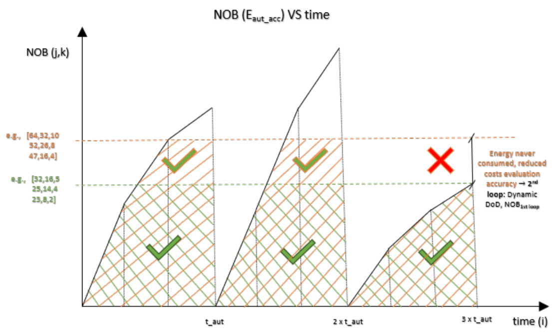


Figure 28: FEM Costs Optimization Concept

In addition to the costs optimization, DOD_{max} and the instantaneous expected DOD, DOD_{inst}, for the optimum solution, or an optimal range of them, is also extracted from the algorithm and considered for further EMS strategy development in future work, when selecting the optimum designs to be represented in a data driven model. It is important to mention that batteries sizing approach is mainly based on the energy demand function constrained for the autonomy selection and the power profile is considered to evaluate system response feasibility. The correspondent code in Matlab for the costs optimization re-adjustment is included in Appendix A.2.

4.0.2 Fossil Fuels Hybrid Mode, FFHM

When evaluating the FFHM in a retrofit project there are on the table two main options, either to keep the existing energy sources and add new ones, e.g. storage elements, or remove the existing installation to go for a complete new power plant solution. The second alternative is not commonly considered under normal circumstances but nowadays, and considering the big amount of emerging technologies, an evaluation of the payback time from the second alternative to comply with new sustainable scenarios or to go for cheaper fuel alternatives is interesting for inclusion. For the presented case study there no access to new installation costs assessment but the structure is ready to be included when required.

For FFHM evaluation desired nominal speed of 750 rpm for Gensets and a Genset application for a Diesel-electricl propulsion plant are defined to get a first scope of solutions considering also as minimums a Tier II IMO emissions regulations compliance.

The present mode is evaluated over the same simplified boxes selection within feasibility and optimization environments. For the present evaluation dimension k is the number of Gensets, NOG options for selection, e.i. 1,2,4 in the present evaluation. The objective variable, NOB in a FEM, is defined as the instantaneous Gensets loading for specific i, load profile step, j, Genset type and k, NOG, as a 3D environment.

At the beginning, from the feasibility environment, a vector of feasible number of Gensets for installation limited by space and weight constraints is extracted. From this vector the user can select some Gensets number, k dimension, already tested feasible from the ship design perspective. These options must be suitable for the system response and the Gensets loading variable is the one which ensures operational feasibility. Then, higher loading values than the maximum Gensets loading specified by design are considered non-feasible but they could change into feasible by increasing the percentage of energy support from the battery each autonomy slot.

From equation 35, space and weight feasibility matrices are not included in an explicit way but they are implicit in the number of Gensets selection remaining explicit operational feasibility in the generic structure:

$$CM_G = CM_{OP} \tag{45}$$

At this point, the Energy Management System strategy starts its role. For a better understanding the main concept for FFHM development is presented in Figure 29.

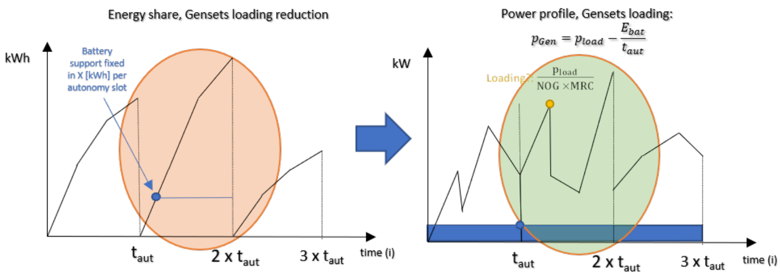


Figure 29: FEM Costs Optimization Concept

The autonomy slot with the highest energy demand is under assessment. To test how accurate is to asses the cost from one autonomy slot, two of them will be tested and compared. The energy released from the battery pack is fixed at a certain amount of kWh support in the quality of a simple load leveling EMS strategy. Then the Gensets loading is recalculated over the whole load profile sample and expecting to be reduced, not necessary together with the final costs. By now this method is considered accurate enough for a first simplification. As long as the costs of the battery pack sizing are already calculated for different maximum energy release it is just the Gensets side the one missing for costs estimation. The way of calculating the costs each point performs same as for FEM considering to repeat the pattern up to the time step of analysis among K years of expected system or ship life.

From equation 38 and just considering machinery costs, $(C_M)_2$, if new machines installation is desired:

$$f_{op_{COST}}(i,j,k) = (f_{op_{COST}})_1(i,j_1,k_1) + (f_{op_{COST}})_2(i,j_2,k_2) \tag{46}$$

$$OPEX(i,j_1,k_1,j_2,k_2) = (C_f)_1(i,j_1,k_1) + (C_{MBR})_1(i,j_1,k_1) + (C_f)_2(i,j_2,k_2) \tag{47}$$

$$CAPEX(i,j_1,k_1,j_2,k_2) = (C_M)_1(i,j_1,k_1) + (C_M)_2(i,j_2,k_2) \tag{48}$$

Being one indexes batteries reference and the new functions form genstes calculation:

$$C_f(i, j_2, k_2) = f_{c_T}(\%rhl(\%_{kWh})) \times C_F \times \frac{kWh}{cycl} \times \frac{K \times 24 \times 365}{t(cycl_{end}) - t(cycl_{start})} \tag{49}$$

$$C_M(i, j_2, k_2) = \mathbf{k_2} \times C_G; \tag{50}$$

Where:

f_{c_T} = fuel consumption each machine selection, as a function of the percentage of working hours at a specific loading, $\%rhl$, which is function at the time of the percentage of energy covered by Gensets, $kWh/cycl$, from the one demanded by the load profile, each autonomy slot. Fuel consumption curves are presented in Appendix B.

C_F = fuel costs for Marine Diesel calculated as around 0.5€/kg.

In the end, the algorithm minimizes the cost function by changing the energy share, considering a basic EMS strategy for load optimization by fixing the amount of energy released by the battery pack each autonomy slot. At the present scope the approach ensures for a design optimization of the power plant selection waiting for further boxes implementation which improves accuracy and considers more number of elements contribution, from the electrical system requirements to the storage volumes, safety levels or novelty of the solution.

It is important to highlight for the present mode that, in contrast with FEM, the power profile is the one which determines the Gensets instantaneous loading, not considered by now to deal with power response problems neither energy storage limitations to linked with autonomy requirements. Nevertheless, future work must link with the fuel consumption and storage volumes required on board, Figure 30. From the costs calculation, machinery block replacement is not considered while, for batteries, it has a great impact. Thus, maintenance costs assessment is essential for a proper final Gensets costs evaluation and it is by not not considered due to lack of data. In addition, new Gensets installation costs are just estimates on what they could be in the market.

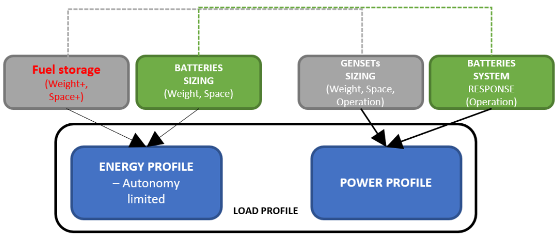


Figure 30: Energy-Power profile system sizing dependencies

4.0.3 Fossil Fuels Mode, FFM

The currently installed power system runs with Catepillar GENSETs which embedded engines are recommended to be driven by Heavy Fuel Oil with Low Heating Values of around 42,780 kJ/kg, [7], and an estimated fuel cost of around 416 \$/mt (0,36€/l) if considering IFO380 marine fuel commonly used, [34].

Fuel consumption curves extracted from C280-8 and 3508B GENSETs, models of Caterpillar catalog with a maximum rated power of 2420 ekW and 910 ekW respectively, are considered. From the simplified fuel costs calculation in equation 51 together with the data included in Figure 31 a result of the expected fuel costs in the following 30 years of the vessel is shown in estimation 52.

$$C_{FK} = \left(\sum_{j=1}^{n} \sum_{k=1}^{m} h_{Tj} \times \frac{perc_{jk}}{100} \times sfc_{jk} \times c_f \right) \times \frac{K}{t_s} \tag{51}$$

s.t.

j = GENSET number $\forall j \in \mathbb{N} \wedge 1 \leq j \leq n$

n = max. number of GENSETs, n = 4 for this case study

k = GENSETs loading slots $\forall k \in \mathbb{N} \wedge 1 \leq k \leq m$

m = max. number of GENSETs' loading slots

$perc_{jk}$ = % of the total running hours each i & j

sfc_{jk} = specific fuel consumption each i & j

h_{Tj} = running hours, each i

c_f = specific fuel cost

K = expected ship life, time left for the retrofit case

t_s = load profile time registered

Table 17 defines the loading slots for this case study.

$$C_{F30} \approx \$63.862M \approx 63,28MEUR \tag{52}$$

For: LLO for MDF	22	% MCR		Total running hours		1056	
For: MCR	assumed =	P_rated					
Ranges	<=LLO	LLO-60%	60%-80%	80%-90%	>90%	Reversed Power	Total Reversed Energy
TOTAL	[%]	[%]	[%]	[%]	[%]	[%]	[kWh]
G1	11.385 %	3.786 %	10.104 %	0.851 %	0.002 %	74.799 %	1556
G2	60.654 %	32.166 %	7.294 %	0.371 %	0.012 %	0.000 %	0.272
G3	59.936 %	33.882 %	3.665 %	2.574 %	0.009 %	0.063 %	0.717
G4	86.095 %	6.134 %	8.292 %	0.108 %	0.006 %	0.000 %	0
From total running hours	54.517 %	18.992 %	6.792 %	0.976 %	0.007 %	18.716 %	1556.989

FUEL CONSUMPTION CURVES

C280-8			3508B		
bkW	%	L/hr	bkW	%	L/hr
2460	100%		**968**	100%	234
2337	95%	624.4		75%	179
2239	91%	589.8		50%	125
2091	85%	562.6			
1474	60%	523.3			
1212	49%	327.7			
950	39%	313.7			
760	31%	252.1			
741	30%	205.8			
532	22%	202.1			

RUNNING HOURS EACH LOADING INTERVAL

120.2235599	39.98155	106.6946	8.984947	0.02639
640.5023473	339.671	77.02055	3.913971	0.123614
632.9223425	357.791	38.70573	27.18274	0.098614
909.1641931	64.77809	87.55905	1.141697	0.061113

FUEL CONSUMPTION L/h *rough approximation for loading intervals*

202.1	327.7	523.3	562.6	624.4
125	125	179	179	234
125	125	179	179	234
202.1	327.7	523.3	562.6	624.4

TOTAL FUEL CONSUMPTION L						TOTAL		
	24297.18145	13101.96	55833.31	5054.931	16.47763	98303.85135		
	80062.79341	42458.88	13786.68	700.6008	28.92561	137037.8766		
	79115.29281	44723.87	6928.325	4865.71	23.07567	135656.2767		
	183742.0834	21227.78	45819.65	642.3186	38.15878	251469.9933		
						622467.9979	**L**	**in 44 days**
						154909649.5	**L**	**in K years**
				IFO380	**(ro)**	**991**	**kg/m3**	
						416	**$/mt**	
					COST	**$ 63,862,432.46**		**54,283,067.59 €**
					EXPECTED LIFE	**30**		**years**

Figure 31: FFM Calculation

5 Results Discussion

Considering that the data inserted into the algorithm is not all necessary data for an accurate final evaluation on the retrofit project, it has been decided to further shorten the load profile steps for evaluation. Thus the computational time changes from some days to just around two hours. The algorithm can be tested this way and also accurate statements can be done over the costs estimation, as long as the sampling time is higher than the autonomy slot selection, e.i. $t_{aut} = 1$ hour and sampling time is equal to half day of operation.

The load profile insertion is reduced into the one in Figure 32.

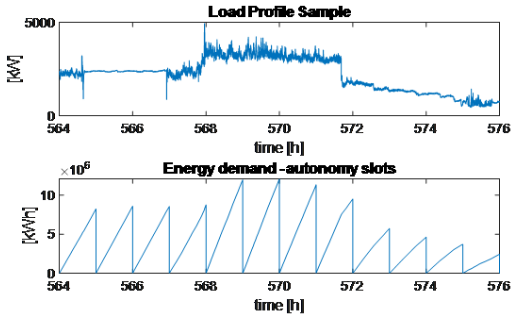


Figure 32: Load Profile Reduced

5.1 FEM

Full electric mode is evaluated within feasibility terms and costs optimum battery pack sizing.

The conference paper published in ITEC2021, relative to the present project, Appendix D, well explains the feasibility environment for different proposed autonomy slots:

Table 19: left-right: NOBs feasibility; NOBs conforming the battery pack each autonomy, DOD_{MAX} and battery type selection

Autonomy [s]	k/j	Weight				Space				Operation_1			
		B1	B2	B3	B4	B1	B2	B3	B4	B1	B2	B3	B4
	0.5	1	1	1	1	1	1	1	1	1	1	1	0
1800	0.8	1	1	1	1	1	1	1	1	1	1	1	0
	1	1	1	1	1	1	1	1	1	1	1	1	0
	0.5	1	1	1	1	1	1	1	1	1	1	1	1
3600	0.8	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	1
	0.5	0	0	0	0	0	0	0	0	1	1	1	1
86400	0.8	0	0	0	0	0	0	0	0	1	1	1	1
	1	0	0	0	0	0	0	0	0	1	1	1	1
	0.5	0	0	0	0	0	0	0	0	1	1	1	1
259200	0.8	0	0	0	0	0	0	0	0	1	1	1	1
	1	0	0	0	0	0	0	0	0	1	1	1	1

Autonomy [s]	**k/j**	***NOB Required (k,j)***			
		B1	**B2**	**B3**	**B4**
	0.5	7600	3040	1520	507
1800	**0.8**	4750	1900	950	317
	1	3800	1520	760	254
	0.5	14328	5731	2866	956
3600	**0.8**	8955	3582	1791	597
	1	7164	2866	1433	478
	0.5	167672	67069	33535	11179
86400	**0.8**	104795	41918	20959	6987
	1	83836	33535	16768	5590
	0.5	468450	187380	93690	31230
259200	**0.8**	292782	117113	58557	19519
	1	234225	93690	46845	15615

The operational feasibility of higher batteries, for small autonomy requirements, could be compromised due to lower speed of response considering a battery pack of the same capacity but less number of batteries when higher capacities are selected. This statement is reflected in table 19. Autonomy requirements of more than some hours are not able to fulfil with the power requirements from operation. For autonomy settings up to an hour the four type of batteries could succeed inside this retrofit project with battery pack from 478 batteries to 14328 number of them.

The optimization environment is further extended here from the first paper approach with new runs and its consequent analysis.

Figures 34 and 35 shown useful design indexes to easily compare between the proposed alternatives. First, the difference between the two loops result manifest the importance of optimizing the algorithm in a second loop inserting the energy measurement error, under its variables dependencies, e.g. NOB, or re-adjusting the DOD maximum fixed for design with an instantaneous DOD. The impact is strongly advise from results as the specific costs comparison from Loop 1 with a maximum of more than 2000 €/kWh to the maximum of around 2 €/kWh in the optimized second Loop. From the total costs the final results are reduced in an order of three but also clearly identify how smaller batteries are affected by the dynamical DOD inclusion making them run at a higher DOD than them maximum for design while higher batteries reduce its capacity detriment during operation by running at lower instantaneous DOD, hence not suffering from nominal capacity detriment most of the cycles. Smaller batteries reduce the total costs difference from its performance for maximum DOD of around 50% to 80% and higher batteries keep closer in costs higher depth of discharges performance.

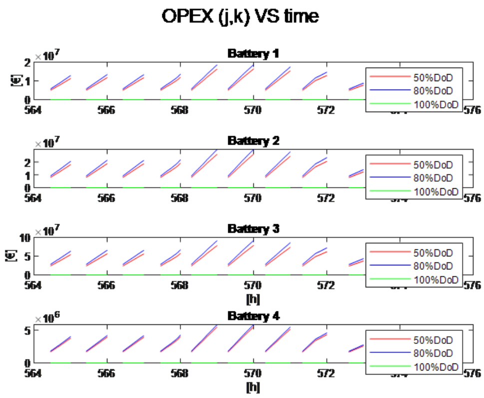


Figure 33: OPEX among time

While OPEX has the greatest impact on the total costs due to battery pack replacement when the battery is considered death, the total costs in Figure 39 presents an scenario where the largest battery, with a nominal capacity of 300 Ah is the cost optimum one with a maximum of 10 M€ during the 30 years of operation from where around half of them corresponds to operational expenses and the rest to a first installation cost and electrical energy consumption at port when re-charging, which is variable dependent on the place to re-charge.

Hence, for the inserted environment a battery pack would be defined as optimum if higher size batteries, of 300 Ah are selected to work at a maximum DOD of design closer to full discharge each cycle. Nevertheless, batteries of 100 Ah nominal capacity are considered more expensive than 50 Ah batteries installation. Then either a battery pack of around 480 batteries of 300 Ah conforming a total installed energy of 1,824 MWh and working for a full depth of discharge at the end of the most demanding autonomy slots, or around 600 batteries with a total energy installed of 2,28 MWh for not going closer to batteries energy release limits, are both feasible and optimum solutions for autonomy slots of one hour under the conditions described during the case study presentation.

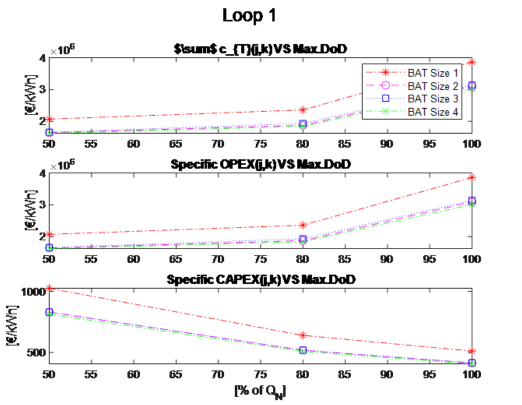


Figure 34: Sum. of spec. costs among the load profile - L1

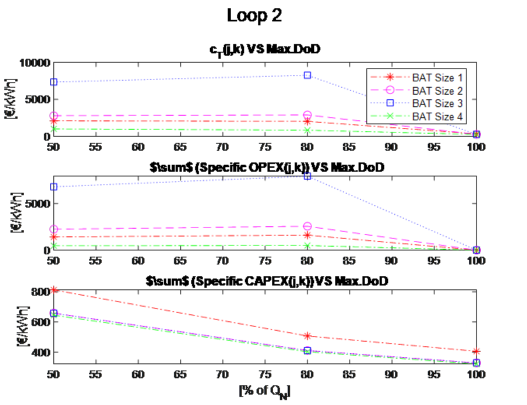


Figure 35: Sum. of spec. costs among the load profile - L2

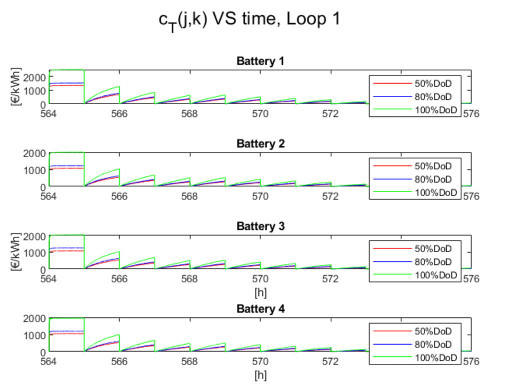


Figure 36: Spec. costs among time - L1

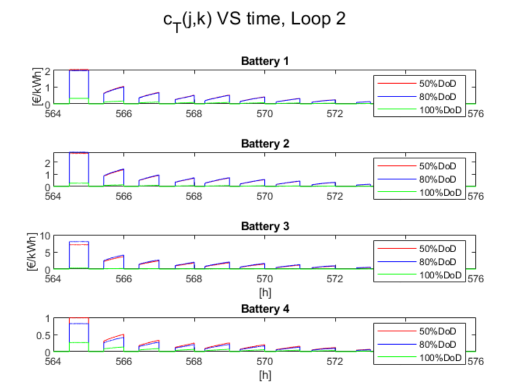


Figure 37: Spec. costs among time - L2

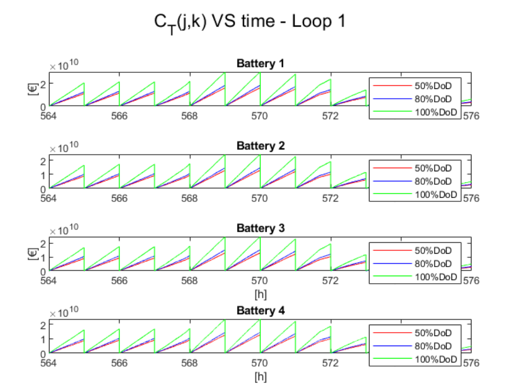


Figure 38: Total costs among time - L1

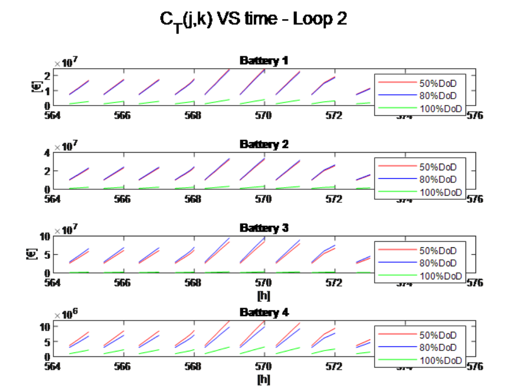


Figure 39: Total costs among time - L2

5.2 FFHM

Results evaluation from the present mode are excluded from the scope due to lack of data to complete a proper analysis or the retrofit project for the hybrid solution. Additional blocks must be added to the cost function from a retrofit project to proceed with a valuable evaluation of the solution. Maintenance assessment of the current diesel-electric installation is essential to evaluate optimum designs. While Full Electric Mode costs are significantly weighted via capacity detriment or expected blocks replacement, generating sets life cycle costs are further identify from maintenance requirements and fuel costs among the ship life for a retrofit assessment. Both modes, FFHM suffer significant impact in the cost function from the initial installation investment (power plant building costs or CAPEX).

6 Conclusions and Future Work

The energy transition "*technical war*" ensures for an interesting maritime scenario which could follow the general worldwide energy transition with two big parties interested in introducing its solutions. On one side, the ambitious companies from the electrical energy production field, and, on the other side, the strong and powerful oil and gas industry with its fossil fuel business core still under exploitation and transformed to confront the new energy transition scenario.

The presented document proposes a solid structure which gathers generic variables and design key indexes for a power plant sizing optimization. The operational profile insertion allows not just to conclude with a final energy sources selection and sizing but also with the consequent operational ranges of the system to keep the system sizing solution between optimum ranges. All data treatment is designed to cover the present algorithm needs and will keep under improvement with further data inclusion. The structure is ready to insert different new assessments in the form of discrete data.

Some parts of the structure are deeply tested while some others keep open for study. Full Eclectic Mode is one part studied in detail, also due to the nature of the input data with enough open source available for a proper analysis applied to the preliminary design of the ship. For the hybrid mode, the structure of calculus is presented but there is not final data evaluation among this potential solution.

A retrofit of an Offshore Supply Vessel is presented for evaluation. The data inserted from the ship is just rough approximation to what the real case can include, specially for the available space at the machinery room or the required autonomy. From the Full Electric Mode, in addition to the conclusions from the paper published linked to the feasibility of the battery pack solution, the optimum sizing is lead by a number of 597 batteries with individual capacity of 300 Ah, working at a maximum DOD of design of 80% each autonomy slot conforming a battery pack of 2,3 MWh of installed energy on board. For 30 years of operation total costs of around 20M most of them due to battery pack replacements under the present batteries life estimation.

Then, also a rough estimation of the fuel consumption for the existing installation is carried out with a resulting 63M just in fuel expenses over that 30 years of operation, without considering maintenance costs, commonly high specially for vessels, as the one under concern, with sharp operational profiles and a swinging machine performing under low loading conditions most of the time.

The main issue from the Full Electric Mode is the autonomy requirements which are ideally set in one our but most commonly it is not possible to re-charge the back of large ships within that frequency ranges. Battery packs solutions for the maritime sector must come together with smaller and faster ship designs and a well planned re-charging infrastructure to aim for high frequency re-charges. Electrical and control systems for batteries pack installation also presents some challenges as a good protection skims design. Safety could be impact, also due to the novelty level of the solution but emissions on-board are reduced to 0.

The next step on the presented project is to fully analyse the hybrid mode and its benefits for a retrofit project, an extensive analysis ready to be implemented in the present algorithm. The load profile estimation module together with artificial intelligence algorithms could extend its application into the first scope of solutions filtering. Relational Data Table algorithm design must be completed continuing from the presented analysis to be inserted in the algorithm.

From a medium to long term perspective a software for the power plant design evaluation could be useful in the industry and an updated data base including the current scenario of solutions would be of added value for the software use.

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Appendix

A EEDI Calculation

- $\underline{EEDI_{attained}}$ [g-CO_2/tone.mile] :

$$\mathbf{EEDI_{attained}} = [\mathbf{ME}(\mathbf{s})\,\mathbf{CO_2} + \mathbf{AE}(\mathbf{s})\,\mathbf{CO_2} + \mathbf{ADD}(\mathbf{s})\,\mathbf{CO_2} - \mathbf{IT}(\mathbf{s})\,\mathbf{CO_2}] \times TW \quad (53)$$

- Main engine(s) CO_2 emissions, $ME(s)\,CO_2$:

$$\mathbf{ME}(\mathbf{s})\,\mathbf{CO_2}\,[\mathbf{t}] = \left(\prod_{\mathbf{j=1}}^{\mathbf{M}} \mathbf{f_j}\right) \times \left(\prod_{\mathbf{i=1}}^{\mathbf{n_{ME}}} \mathbf{C_{FME_i}} \times \mathbf{SFC_{ME_i}} \times \mathbf{P_{ME_i}}\right) \quad (54)$$

Where:

C_{FME_i} = conversion factor fuel oil to CO_2.

SFC_{ME_i} = specific fuel oil consumption of the main engine at 75% MCR acc. to NOx Technical File.

P_{ME} = 75% of MCR (to its EIAPP certificate). If a shaft generator is installed two options are available to calculate its effect:

1. MCR of the main engine can be reduced by P_{PTO_i} but not more than the maximum value of P_{AE} (define in the rule). Then, $P_{ME} = 75\%(MCR_{(i)} - P_{PTO})$. With $P_{PTO} = 75\% P_{rated-shaft})$
2. When an engine is installed with higher rated power output than the propulsion system is limited to by verified technical means. Then, $P_{ME_i} = 75\% P_{shaft-limit}$.

i = each installed engine.

j = each specific design element.

f_j = correction factor to account for ship specific design elements. Dependent on P_{ME}.

n_{ME} = number of installed main engines.

M = total number of specific design elements.

- Auxiliary engine(s) CO_2 emissions, $AE(s)\,CO_2$:

$$\mathbf{AE}(\mathbf{s})\,\mathbf{CO_2}\,[\mathbf{t}] = \mathbf{C_{FAE}} \times \mathbf{SFC_{AE}} \times \mathbf{P_{AE}} \quad (55)$$

Where:

C_{FAE_i} = analogous to use as describe for the main engine and if installing different engines running with different fuel types equal to:

$$C_{FAE} = \frac{\sum_{i=1}^{n_{AE}} C_{FAE(i)} \times MCR_{AE(i)}}{\sum_{i=1}^{n_{AE}} MCR_{AE(i)}} \quad (56)$$

SFC_{AE} = weighted average among $SFC_{AE(i)}$ of the respective auxiliary engines i:

$$SFC_{AE} = \frac{\sum_{i=1}^{n_{AE}} SFC_{FAE(i)} \times MCR_{AE(i)}}{\sum_{i=1}^{n_{AE}} MCR_{AE(i)}} \quad (57)$$

Considering part of the P_{AE} provided by the shaft generator, if $P_{PTO} \geq P_{AE}$, equation 55 becomes:

$$AE(s)\, CO_2\, [t] = C_{FAE} \times \mathbf{SFC_{ME}} \times P_{AE} \tag{58}$$

if $P_{PTO} \leq P_{AE}$ *(inconsistency from regulation)*, equation 55 becomes:

$$AE(s)\, CO_2\, [t] = C_{FME} \times \mathbf{SFC_{ME}} \times P_{PTO} + C_{FAE} \times \mathbf{SFC_{AE}}\, (P_{AE} - P_{PTO}) \tag{59}$$

P_{AE} = auxiliary power demanded for the operation of the main engine(s) and calculated as a share of the installed main engine power, being calculated as:

$$P_{AE(MCR(ME)>10000kW)} = \left(0.025 \left(\sum_{i=1}^{nME} MRC_{ME} + \frac{\sum_{i=1}^{nPTI} P_{PTI(i)}}{0.75}\right)\right) + 250 \tag{60}$$

$$P_{AE(MCR(ME)<10000kW)} = 0.05 \left(MRC_{ME} + \frac{\sum_{i=1}^{nPTI} P_{PTI(i)}}{0.75}\right) \tag{61}$$

- Additional emissions:

  Coming from shaft motors, new electrical energy efficient technology and ice class design restrictions:

$$\mathbf{ADD(s)\, CO_2\, [t]} = \left(\prod_{\mathbf{j=1}}^{\mathbf{M}} \mathbf{f_j} \sum_{\mathbf{i=1}}^{\mathbf{nPTI}} \mathbf{P_{PTI(i)}} - \sum \mathbf{f_{eff(i)} P_{AEeff(i)}}\right) \mathbf{C_{FAE}} \times \mathbf{SFC_{AE}} \tag{62}$$

  Being,

$$P_{PTI(i)} = 0.75 \times \frac{rated\, power\, shaft\, motor(i)}{\eta_{Gen}} \tag{63}$$

$$\eta_{Gen} = \frac{\sum_{i=1}^{nAE} \eta_{Gen(i)} \times (P_{out_{rated}})_{Gen(i)}}{\sum_{i=1}^{nAE} (P_{out_{rated}})_{Gen(i)}} \tag{64}$$

  f_{AEeff} = availability factor each innovative technology calculated according to Annex D of [21].

  P_{AEeff} = auxiliary power reduction due to innovative electrical energy efficient technology measured at $P_{ME(i)}$ given in Annex D of [21].

- Innovative technologies' CO_2 emissions reduction, $IT(s)\, CO_2$:

  Part of the engine power delivery could be reduced and supplied by different innovative technologies. The CO_2 emissions reduction term is calculated as it follows:

$$\mathbf{IT(s)\, CO_2} = \sum_{\mathbf{i=1}}^{\mathbf{n_{eff}}} \mathbf{f_{eff(i)}} \times \mathbf{P_{eff(i)}} \times \mathbf{C_{FME}} \times \mathbf{SFC_{ME}} \tag{65}$$

  Where:

$$P_{eff} = P_{PeffAL} - P_{AEeffAL} \left(\frac{C_{FAE} \times SFC_{AE}}{C_{FME} \times SFC_{ME}}\right) \tag{66}$$

  P_{PeffAL} = reduction of propulsion power due to air lubrication system at V_{ref}.

  $P_{AEeffAL}$ = additional auxiliary power demand necessary to run the air lubrication system at 75% of the rated output of the blower based on manufacturer's test report.

Equations 53, 54, 55 and 54 are all added up to EEDI's calculation and divided by transport worK. The transport work, TW from equation 53, is calculated multiplying Capacity and reference speed, V_{ref}, at EEDI conditions, considering the power output each element. Capacity and speed are multiplied by tree different factors regarding capacity correction accounting for ship specific design elements, general cargo ships and chemical tankers, and a factor regarding speed detriment due to sea conditions. In case where shaft motor(s) are installed, V_{ref} shall be determined at:

$$\sum P_{ME(i)} + \sum P_{PTI(i),shaft} \tag{67}$$

Being:

$$\sum P_{PTI(i),shaft} = \sum \left(P_{PTI(i)} \times \eta_{PTI(i)}\right) \times \eta_{Gen} \tag{68}$$

B Machinery Raw Data

A Gensets

Tables 20 and 21 includes the input data to the algorithm for the present project scope. This first steps allows to identify open source data from manufacturers and the missing data required for algorithm implementation and accuracy improvement.

Caterpillar open source data is limited and, although not all desired variables are accessible MAN marine engines include the engines project guidelines from where to extract more data. General variables as it is power or speed ratings or nominal values are open for evaluation while control factors, from integrated ECU or machinery response limits are not that easy to get. As expected prices of the engines are not available so they are just estimated for the purpose of algorithm development and testing.

Table 20: Gesnsets selection for algorithm testing

			PARAMETERS			
			Add option	Installed		Add option
	CATERPILLAR Diesel-Electric Propulsion (Genset)		C18 (prop.)	C32	3516C	C280-16
		bkW	599.00	994.00	2350.00	5060
		rpm	1800	1800	1800	900
	EQUIVALENT MAN Diesel-Electric Propulsion (Genset)		5L23/30DF	8L23/30DF	8L27/38	9L32/44CR
		bkW	625	1000	2640	5040
		rpm	750	750	750	750
	TIER (1.I/2.II/3.III)	IMO	3	2 (without scrubber)	2 (without scrubber)	2 (without scrubber)
	CO2 max. max approx.	g/kWh	620	620	620	620
	NO2 max. max approx.	g/kWh	5160	5160	5160	5160
At rated power and withouth exhaust gas treatment	SOx max. max approx.	g/kWh	10.00	10.00	10.00	10.00
	NOX max. max approx.	g/kWh	10.00	10.00	10.00	10.00
	CO max. approx.	g/kWh	0.80	0.80	0.80	0.80
	HC max. approx.	g/kWh	1.20	1.20	1.20	1.20
	PM (HFO) max approx.	g/kWh	0.59	0.59	0.59	0.59
	PM (MGO) max approx.	g/kWh	0.35	0.35	0.35	
	Stop at	% of MRC	110	110	110	110
	Dry Weight	tonnes	17.3	23.4	58.2	53.5
	Length	mm	5671	7248	8667	7984
	Width	mm	1210	1210	1770	1790
	Height	mm	2749	2749	3899	4369
	Fuel LHV	kJ/kg	42700	42700	42700	42700
	Cost	€	€ 100,000.00	€ 200,000.00	€ 300,000.00	€ 500,000.00
	max speed drop	% of rpm_nominal	-	-	-	-
	Min. time to max. P_inst	s	-	-	-	-

Table 21: Fuel consumption from Gensets selection in g/kWh.

Model	5L23/30H	5L23/30H	8L27/38	9L32/44CR
rpm	750	750	750	750
100	194	194	184	178
85	193	193	182	176
75	192	192	182	180
50	196	196	184	188
25	218	218	204	204

B Batteries

Table 22 illustrates the data inserted from battery selection to test the algorithm. Bateries data sheets include more open source data than Generating Sets, as expected. In addition to the data inserted here, curves with different battery measurements under specified conditions are available from the sheets. They include charge voltage curves and SOC at a specific C-rate over time, charge voltage curves at different temperatures but also at a fixes C-rate and discharge voltage curves also at different temperature conditions and a fix C-rate. These curves are not used by now but the one with the capacity reduction per cycle is inserted into the algorihtm and deeper analysed in Section 3.1. With the available data it is possible already to perform an interesting superficial analysis with strong conclusions.

Table 22: Batteries selection for algorithm testing

		1	2	3	4	5	6	7
Battery tag		RelLIH1	RelLIH2	RelLIH3	RelLIC1	RelLIC2	RelLIC3	RelLIC4
Cold weather		0.00	0.00	0.00	1.00	1.00	1.00	1.00
Application		HT	HT	HT	LT	LT	LT	LT
Chemistry		Lithium-ion	Lithium-ion	Lithium-ion	Lithium-ion	Lithium-ion	Lithium-ion	Lithium-ion
Nominal Voltage	V	12.80	12.80	12.80	12.80	12.80	12.80	12.80
Nominal Capacity	Ah	50.00	100.00	300.00	20.00	50.00	100.00	300.00
Energy	kWh	0.58	1.15	3.46	0.23	0.58	1.15	3.46
Capacity @25A	min	120.00	240.00	720.00	48.00	120.00	240.00	720.00
Max. Internal resistance	m	50.00	30.00	30.00	45.00	50.00	30.00	30.00
Efficiency	%	90.00	90.00	90.00	90.00	90.00	90.00	90.00
Max. self discharge per month	%	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Maximum modulus in series		1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max. continuous discharge current	A	50.00	100.00	100.00	20.00	50.00	100.00	100.00
Max. peak discharge current	A	400.00	800.00	800.00	40.00	100.00	200.00	200.00
	-	0.13	0.13	0.38	0.50	0.50	0.50	1.50
Peak discharge current time $\leq$	s	3.00	2.00	2.00	7.50	7.50	7.50	7.50
Min. recommended charge current	A	2.50	5.00	15.00	1.00	2.50	5.00	15.00
Max. recommended charge current	A	25.00	50.00	50.00	10.00	25.00	50.00	50.00
Maximum charge current	A	50.00	100.00	100.00	20.00	50.00	100.00	100.00
Min. recommended charge voltage	V	14.20	14.20	14.20	14.20	14.20	14.20	14.20
Max. recommended charge voltage	V	14.60	14.60	14.60	14.60	14.60	14.60	14.60
Max. C for -10ºC - 0ºC	C	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Max. C for -20ºC - - 10ºC	C	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Max recomended DOD	%	30.00	30.00	30.00	30.00	30.00	30.00	30.00
Cycle life at DOD 50%		13000.00	13000.00	13000.00	13000.00	13000.00	13000.00	13000.00
Cycle life at DOD 80%		7100.00	7100.00	7100.00	7100.00	7100.00	7100.00	7100.00
Cycle life at DOD 100%		3600.00	3600.00	3600.00	3600.00	3600.00	3600.00	3600.00
Cost		528.96	1091.06	3033.20	275.63	558.76	1116.73	3279.07
Weight	kg	8.50	13.50	37.50	3	6.38	12.64	34.54
Lenght	m	0.26	0.33	0.52	0.18	0.20	0.33	0.52
Wide	m	0.17	0.17	0.27	0.08	0.17	0.17	0.27
Depth	m	0.22	0.22	0.23	0.17	0.17	0.22	0.23
FOR REAL TIME DATA EVALUATION/EMBEDED CONTROL			**NEXT DEVELOPMENT STEP**					
BMS Discharge Current Cut-Off	A	550.00	1000.00	1000.00	50.00	150.00	280.00	280.00
BMS Discharge Current Cut-Off +/-	A	60.00	100.00	100.00	8.00	20.00	50.00	50.00
BMS Discharge Current Cut-Off, time	ms	42.00	2.20	2.20	32.00	10.00	32.00	9.00
BMS Discharge Current Cut-Off +/- , time	ms	22.00	1.00	1.00	8.00	5.00	10.00	4.00
Recommended Low Voltage Disconnect	V	11.00	11.00	11.00	11.00	11.00	11.00	11.00
BMS Discharge Voltage Cut-Off	V	8.00	9.20	9.20	8.00	9.20	9.20	8.00
BMS Discharge Voltage Cut-Off, vpc	vpc	2.00	2.30	2.30	2.00	2.30	2.30	2.00
BMS Discharge Voltage Cut-Off +/−, vpc	vpc	0.08	0.08	0.08	0.08	0.10	0.08	0.08
BMS Discharge Voltage Cut-Off, time	ms	100.00	4200.00	4200.00	20.00	140.00	4700.00	140.00
BMS Discharge Voltage Cut-Off +/−, time	ms	50.00	500.00	500.00	8.00	60.00	1000.00	60.00
Reconnect Voltage dicharge	V	10.00	10.00	10.00	9.04	10.00	10.00	9.20
Reconnect Voltage dicharge, vpc	vpc	2.50	2.50	2.50	2.26	2.50	2.50	2.30
Reconnect Voltage dicharge +/−, vpc	vpc	0.10	0.10	0.10	0.34	0.10	0.10	0.10
Short Circuit Protection	s	200.00	200.00	200.00	100.00	200.00	200.00	200.00
	s	800.00	600.00	600.00	600.00	600.00	600.00	600.00
BMS Charge Voltage Cut-Off	V	15.20	15.40	15.40	15.60	15.40	15.40	15.60
BMS Charge Voltage Cut-Off, vpc	vpc	3.80	3.85	3.85	3.90	3.85	3.85	3.90
BMS Charge Voltage Cut-Off +/-, vpc	vpc	0.05	0.03	0.03	0.03	0.03	0.03	0.05
BMS Charge Voltage Cut-Off, time	s	1.00	1.00	1.00	1.00	1.10	1.00	1.00
BMS Charge Voltage Cut-Off +/-, time	s	0.50	0.20	0.20	0.30	0.40	0.20	0.50
Reconnect Voltage charge	V	14.40	14.60	14.60	14.60	14.60	14.60	15.20
Reconnect Voltage charge, vpc	vpc	3.60	3.85	3.65	3.80	3.65	3.65	3.80
Reconnect Voltage charge +/−, vpc	vpc	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Balancing Voltage charge	V	14.40	14.40	14.40	14.40	14.40	14.40	14.40
Balancing Voltage charge, vpc	vpc	3.60	3.60	3.60	3.60	3.60	3.60	3.60
Balancing Voltage charge +/−, vpc	vpc	0.03	0.03	0.03	0.03	0.03	0.03	0.03

C Algorithm Matlab Code

A FEM

A.1 1_{st} LOOP

morekeywords

```
%%FULLY ELECTRICAL MODE-------------------FIRST EVALUATION LOOP

tic;
initime = cputime;
time1   = clock;
pause(1.0);                     % Wait for a second;
fintime = cputime;

%%%Project data
SOVProjectdata_1 = readtable('PC3_SOV.xlsx');
SOVProjectdata_1.Name = str2double(SOVProjectdata_1.Name);
SOVProjectdata_1.units = str2double(SOVProjectdata_1.units);
SOVProjectdata_1.add_info = str2double(SOVProjectdata_1.add_info);
SOVProjectdata = table2array (SOVProjectdata_1);
Fuel_Cost_1 = readtable('fuel_costs.xlsx');
Fuel_Cost_1.TYPE = str2double(Fuel_Cost_1.TYPE);
Fuel_Cost_1.units = str2double(Fuel_Cost_1.units);
Fuel_Cost = table2array (Fuel_Cost_1);

%%%1-Application/Type/Brand/(MUST BE ELABORATED)%%Add for more than one
%%%range. Automate this.--------------------------%%%INTRODUCE CURVE
%%%FITTING METHOD

range_1_1=4;%this one must be automatize (including rules constraints)
range_1_2=7;

battery_selection_1 = range_1_1:1:range_1_2;
[m_b, size_feasible_battery_matrix_1] = size(battery_selection_1);


%RELATIONAL-DATA----------STRATEGY TO DEVELOP AND INCLUDE

rtc_machinery_installation_weight = (SOVProjectdata(37,2)+SOVProjectdata(44,2)+
    SOVProjectdata(50,2))/1000;
max_machinery_weight_increment = 2; %due to max. speed design limitations [get the
    best curve fitting]
WEIGHT_machinery_installation_2 = (rtc_machinery_installation_weight + (
    rtc_machinery_installation_weight*max_machinery_weight_increment))*1000;
%
    ------------------------------------------------------------------------------------------------

%%%2-Constraint environment
t_autonomy(1,1) = t_m;
E_d_autonomy(1,1)= E_d_tm(1,1);
for i=2:n
    if t_autonomy(i-1,1) < SOVProjectdata(21,2)
        t_autonomy(i,1) = t_autonomy(i-1,1) + t_m;
        E_d_autonomy(i,1) = E_d_autonomy(i-1,1) + E_d_tm(i,1);
    else
        t_autonomy(i,1) = t_m;
        E_d_autonomy(i,1) = E_d_tm(i,1);
```

```
    end
end

%----------------------------------------FEASIBLE DIMENSIONS
%----------------------------------------FEASIBLE SIZE
%----------------------------------------FEASIBLE WEIGHT (speed limit or client desired,
%the most restrictive chosen in the algorithm
%just for data analysis MAX
%limited by speed decrement from the project one//optimized (MUST BE ADDED)

%%%%% WEIGHT-SPACE CONSTRAINTS ----------------------------------------------------------------------------

    if ~(0==SOVProjectdata(29,2))
        L_margin = SOVProjectdata(29,2);
    else
        L_margin = SOVProjectdata(26,2);
    end

    if ~(0==SOVProjectdata(30,2))
        W_margin = SOVProjectdata(30,2);
    else
        W_margin = SOVProjectdata(27,2);
    end

    if ~(0==SOVProjectdata(31,2))
        D_margin = SOVProjectdata(31,2);
    else
        D_margin = SOVProjectdata(28,2);
    end
        Space_margins=[L_margin,W_margin,D_margin];



 %LOOP1------------------------------------------------------------------------------

 %Self discharge considered (%per month given)
 %Lineal discharge per cycle considered (%per month given); error incl.
 %NEEDs to be re-structured for speed minimization
 %

 DOD_max=[0.5 0.8 1];
 [mDOD,nDOD] = size(DOD_max);
 number_of_cycles_year = (sum(t_autonomy(:) == t_m)-1)/((t_s(n)-t_s(1))/(3600*24*365)); %number of cycles per year
 MAX_NUMBER_of_batteries_per_dim_SIZE =zeros(3,size_feasible_battery_matrix_1);
 MAX_NUMBER_of_batteries_WEIGHT =zeros(size_feasible_battery_matrix_1,nDOD);
  for j=1:size_feasible_battery_matrix_1 %%THIS ONE MUST BE AUTOMATIZE
        for d = 1:3
            if SOVProjectdata(33,2)==1
                MAX_NUMBER_of_batteries_per_dim_SIZE(d,j)= round(SOVProjectdata(22+d,2)*(1-Space_margins(d))/Batteries_parameters(27+d,battery_selection_1(j)+2));%%take care when this is updated
            else
                shift_oriented=[1,-1,0]; %CLICK
                MAX_NUMBER_of_batteries_per_dim_SIZE(d,j) = round(SOVProjectdata(22+d,2)*(1-Space_margins(d))/Batteries_parameters(27+d+shift_oriented(d),battery_selection_1(j)+2));%%take care when this is updated
            end
```

```
        end
  end
for k = 1:nDOD
  for j=1:size_feasible_battery_matrix_1
        if SOVProjectdata(32,2)<WEIGHT_machinery_installation_2
                MAX_NUMBER_of_batteries_WEIGHT(j,k) = round(SOVProjectdata(32,2)/Batteries_parameters(27,battery_selection_1(j)+2));%%take care when this is updated
            else
                MAX_NUMBER_of_batteries_WEIGHT(j,k) = round(WEIGHT_machinery_installation_2/Batteries_parameters(27,battery_selection_1(j)+2));%%take care when this is updated
        end
  end
end
max_depth=zeros(size_feasible_battery_matrix_1);
MAX_NUMBER_of_batteries_SIZE=zeros(size_feasible_battery_matrix_1,nDOD);
TBM_Battery_replacement=zeros(size_feasible_battery_matrix_1,nDOD);
for k = 1:nDOD
  for j=1:size_feasible_battery_matrix_1
        max_depth(j) = (1 - Batteries_parameters(31,battery_selection_1(j)+2)/100);
        MMC = 2;%%%METHOD MEAN CALCULATION_this can be a parameter of selection or can be based in the error
        MAX_NUMBER_of_batteries_SIZE(j,k) = MAX_NUMBER_of_batteries_per_dim_SIZE(1,j) * MAX_NUMBER_of_batteries_per_dim_SIZE(2,j) * MAX_NUMBER_of_batteries_per_dim_SIZE(3,j);
        TBM_Battery_replacement(j,k) = max_depth(j) / ((Q_reduction_per_cycle_mean(MMC,3*j+k-3))* number_of_cycles_year);  %Qmaxdepth/Qdetrimnt + ERROR_kWh_cycle(MMC,3*j+k-3)
  end
end
month = 30 * 24 * 3600; %co

E_d_meas_error = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
E_d_meas_error_accum_autonomy = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
E_d_meas_error_accum = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
NOB = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
epsilon_NOB_E_d_meas_error = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
Maintenance_costs = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
energy_producers_costs = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
fuel_costs = zeros(n-1,size_feasible_battery_matrix_1,nDOD);

for k = 1:nDOD

  for j=1:size_feasible_battery_matrix_1

      months_counter = 0;
      l = 1;

        for i=1:n-1

E_d_meas_error(1,j,k) = 0;
E_d_meas_error_accum_autonomy(1,j,k) = 0;
E_d_meas_error_accum(1,j,k) = 0;

            if t_s(i) > month*l
                months_counter = months_counter + 1;
                l=l+1;
            end


```

```
max_self_discharge_total = (Batteries_parameters(10,battery_selection_1(j)+2)/100)*(Batteries_parameters(6,battery_selection_1(j)+2))*months_counter;

c=0;
if t_autonomy(i)==t_m %%%when battery is change, detriment go back to 0 (missing to add)
    c = c+1;
end

NOB(i,j,k) = ceil((E_d_autonomy(i)/3600)/((DOD_max(k)*(Batteries_parameters(6,battery_selection_1(j)+2))) - max_self_discharge_total - (((((Q_reduction_per_cycle_mean(MMC,3*j+k-3)/100) * Full_Q_nominal(1,3*j+k-3))+ERROR_kWh_cycle(MMC,3*j+k-3))*c))));
max_speed_discharge = Batteries_parameters(13,j+2)*NOB(i,j,k)*Batteries_parameters(4,j+2)/Batteries_parameters(14,j+2);
E_d_meas_error (i+1,j,k) = abs(p_d(i+1)-p_d(i))*(((max_speed_discharge*t_m) - abs(p_d(i+1)-p_d(i)))/(2*max_speed_discharge));%%INCLUDE ERROR LOOP WITH WHILES
E_d_meas_error_accum (i+1,j,k)  = E_d_meas_error_accum (i,j,k) + E_d_meas_error(i+1,j,k);

                  if t_autonomy(i,1) < SOVProjectdata(21,2)
           E_d_meas_error_accum_autonomy(i+1,j,k) = E_d_meas_error_accum_autonomy(i,j,k) + E_d_meas_error(i+1,j,k);
                      else
           E_d_meas_error_accum_autonomy(i+1,j,k) = E_d_meas_error(i+1,j,k);
                  end

           epsilon_NOB_E_d_meas_error(i,j,k) = E_d_meas_error_accum_autonomy(i,j,k)/3600 /((DOD_max(k)*(Batteries_parameters(6,battery_selection_1(j)+2))) - max_self_discharge_total - ((((Q_reduction_per_cycle_mean(MMC,3*j+k-3)/100) * Full_Q_nominal(1,3*j+k-3))+ ERROR_kWh_cycle(MMC,3*j+k-3))*c));%ERROR_kWh_cycle(MMC,3*j+k-3))
           %rtn_installed_power_nominal(i,j)= NOB(i,j,k)*(Batteries_parameters{6,battery_selection_1(j)+2})/(t_autonomy(i)/3600);   %by now just info consider to realocate
           Maintenance_costs(i,j,k) = (SOVProjectdata(51,2)/TBM_Battery_replacement(j,k))* (NOB(i,j,k) + epsilon_NOB_E_d_meas_error(i,j,k)) * Batteries_parameters(26,battery_selection_1(j)+2); %%SIMPLIFIED into machinery_blocks_replacement_costs(i,j)
           energy_producers_costs(i,j,k) = (NOB(i,j,k) + epsilon_NOB_E_d_meas_error(i,j,k)) * Batteries_parameters(26,battery_selection_1(j)+2);
           fuel_costs(i,j,k) = ( E_d(i) + E_d_meas_error_accum(i,j,k) ) /3600 * Fuel_Cost(2,3) * SOVProjectdata(51,2) / ((t_s(i)-t_s(1))/3600*24*365);

        end

  end

end

%%%FEASIBILITY------------------------------------------------------------
FEASIBLE_SPACE = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
FEASIBLE_WEIGHT = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
FEASIBLE_OPERATION_1 = zeros(n-1,size_feasible_battery_matrix_1,nDOD);

for k = 1:nDOD
  for j=1:size_feasible_battery_matrix_1
        for i=1:n-1
```

```
                    if MAX_NUMBER_of_batteries_SIZE(j,k) < NOB(i,j,k)
                 FEASIBLE_SPACE(i,j,k) = 0; %%%include power electronics space and fuel_storage (in-out)
                    else
                 FEASIBLE_SPACE(i,j,k) = 1;
                    end

                    if MAX_NUMBER_of_batteries_WEIGHT(j,k) < NOB(i,j,k)
                 FEASIBLE_WEIGHT(i,j,k) = 0;
                    else
                 FEASIBLE_WEIGHT(i,j,k) = 1;
                    end

                 E_d_error_SIGN = sign(E_d_meas_error);
                 %inegatif_10=sum(s_10(:)==-1);
                    if E_d_error_SIGN(i,j,k) == -1
                 FEASIBLE_OPERATION_1(i,j,k) = 0; %%%BATTERY PACK SPEED RESPONSE
                    else
                 FEASIBLE_OPERATION_1(i,j,k) = 1;
                    end
        end
  end
end
%%INCLUDE HOW CLOSE TO FEASIBILITY YOU ARE
%%%%%LIFE(n of cycles) VS DOD // %%%%%COST+FINAL RESULT
%%After analysis this will be conditioned for optimization

OPEX = fuel_costs + Maintenance_costs;
CAPEX =  energy_producers_costs;
TOTAL_COST = OPEX + CAPEX;

E_d_selection = repmat(E_d(1:n-1), 1, size_feasible_battery_matrix_1, nDOD);
p_d_selection = repmat(p_d(1:n-1), 1, size_feasible_battery_matrix_1, nDOD);

OPEX_per_power_unit = OPEX./p_d_selection;
OPEX_per_energy_unit = OPEX./E_d_selection;%no much sense this one

CAPEX_per_power_unit = CAPEX./p_d_selection;
CAPEX_per_energy_unit = CAPEX./E_d_selection;%no much sense this one

TOTAL_COST_per_power_unit = TOTAL_COST./p_d_selection;
TOTAL_COST_per_energy_unit = TOTAL_COST./E_d_selection;%no much sense this one

FEASIBLITY = FEASIBLE_SPACE.*FEASIBLE_WEIGHT.*FEASIBLE_OPERATION_1;

%%%Add energy error measurement to the algorithm with a closed loop up to find a trade-off
%%%NOB/E_d_autonomy (THIS IS THE LEVELING)

%%add first seleccion per brand
%%consider modify DOD
%%BUT FIRST JUST ADD THE OPTIMIZATION AND HYBRID PART
%%%3-Operaton feasibility further evaluation?
NOB_MIN=min(min(NOB));
FEASIBILTY_OUT_NOB = transpose(squeeze(max(NOB)));
FEASIBILTY_MATRIX_1 = [min(FEASIBLE_SPACE),min(FEASIBLE_WEIGHT),min(FEASIBLE_OPERATION_1)];
FEASIBILTY_MATRIX_1_text = transpose(squeeze(FEASIBILTY_MATRIX_1));

elapsed = toc;
time2   = clock;
```

```
fprintf('TIC TOC: %g\n', elapsed);
fprintf('CPUTIME: %g\n', fintime - initime);
fprintf('CLOCK:   %g\n', etime(time2, time1));

%We are in: 108 sec.
```

A.2 2_{nd} LOOP

```
morekeywords
%%COSTS OPTIMIZATION - SECOND LOOP
tic;
initime = cputime;
time1   = clock;
pause(1.0);                    % Wait for a second;
fintime = cputime;

clear Maintenance_costs_2
clear energy_producers_costs_2
clear fuel_costs_2

clear Maintenance_costs_3
clear energy_producers_costs_3
clear fuel_costs_3

clear TBM_Battery_replacement_2
clear max_speed_discharge_2

clear DOD_DYN
clear DOD_DYN_ERROR

%NOB_C = NOB.*FEASIBLITY;
OPEX_C = OPEX.*FEASIBLITY;
CAPEX_C = CAPEX.*FEASIBLITY;
TOTAL_COST_C = TOTAL_COST.*FEASIBLITY;
OPEX_per_energy_unit_C = OPEX_per_energy_unit.*FEASIBLITY;
CAPEX_per_energy_unit_C = CAPEX_per_energy_unit.*FEASIBLITY;
TOTAL_COST_per_energy_unit_C = TOTAL_COST_per_energy_unit.*FEASIBLITY;

%----COST RE-CALCULATION BOUND
Maximum_NOBS_count = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
for k = 1:nDOD
    for j=1:size_feasible_battery_matrix_1
        for i=3:n-1
Maximum_NOBS_count(1,j,k)=100000000000;
Maximum_NOBS_count(2,j,k)=100000000000;
Maximum_NOBS_count(3,j,k)=100000000000;
if t_autonomy(i) == t_m
Maximum_NOBS = NOB(i-1,j,k);
else
Maximum_NOBS = 100000000000;
end
Maximum_NOBS_count(i,j,k)=Maximum_NOBS;
        end
    end
end

Min_max_NOBS_sqn = min(Maximum_NOBS_count);
Min_max_NOBS = squeeze(Min_max_NOBS_sqn); %%NOB1bound

```

```
%----FEASIBLITY BOUND
NOB_C = NOB.*FEASIBLITY;
NOBs_feasible_max = squeeze(max(NOB_C));%%NOB2bound

month = 30 * 24 * 3600;
Maintenance_costs_3 = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
energy_producers_costs_3 = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
fuel_costs_3 = zeros(n-1,size_feasible_battery_matrix_1,nDOD);

Maintenance_costs_3_plus = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
energy_producers_costs_3_plus = zeros(n-1,size_feasible_battery_matrix_1,nDOD);
fuel_costs_3_plus = zeros(n-1,size_feasible_battery_matrix_1,nDOD);


for k = 1:nDOD
    for j = 1:size_feasible_battery_matrix_1
      months_counter = 0;
      l = 1;
        for i = 1:n-1
            NOB_1 = NOB(i,j,k);
            remain_year = t_s(i)/3600/24/365;

            if t_s(i) > month*l
                months_counter = months_counter + 1;
                l=l+1;
            end

    if NOBs_feasible_max(j,k) > Min_max_NOBS(j,k)

        if NOBs_feasible_max(j,k) < NOB_1
Maintenance_costs_3(i,j,k) = 0;
energy_producers_costs_3(i,j,k) = 0;
fuel_costs_3(i,j,k) = 0;
        else
                if NOB_1 < Min_max_NOBS(j,k)
Maintenance_costs_3(i,j,k) = Maintenance_costs(i,j,k);
energy_producers_costs_3(i,j,k) = energy_producers_costs(i,j,k);
fuel_costs_3(i,j,k) = fuel_costs(i,j,k);
                else

for k_in = 1:nDOD
    for j_in = 1:size_feasible_battery_matrix_1

        max_depth_2=(1 - Batteries_parameters(31,battery_selection_1(j_in)+2)/100);

        for iplus = 1:n-1

max_self_discharge_total_2 = (Batteries_parameters(10,battery_selection_1(j_in)+2)
    /100)*(Batteries_parameters(6,battery_selection_1(j_in)+2))*months_counter;


DOD_DYN_ERROR = 0;
Q_reduction_per_cycle_mean_2 = 0;
Q_reduction_per_cycle_mean_accum_2 = 0;
TMB_replacements_calcul = 0;
number_of_cycles_year_1=0;
number_of_cycles_year_2=0;
number_of_cycles_year_3=0;
number_of_cycles_year_4=0;
Q_reduction_per_cycle_mean_2_1 =0;
Q_reduction_per_cycle_mean_2_2=0;
```

```
Q_reduction_per_cycle_mean_2_3=0;
Q_reduction_per_cycle_mean_2_4=0;

DOD_DYN =((E_d_autonomy(iplus)/3600)+(NOB_1*(max_self_discharge_total_2 + (
    Q_reduction_per_cycle_mean_accum_2*Full_Q_nominal(1,3*j_in+k_in-3)))))/(NOB_1*(
    Batteries_parameters(6,battery_selection_1(j_in)+2)));

while DOD_DYN_ERROR ~= DOD_DYN %or((DOD_DYN_ERROR < (0.80*DOD_DYN)),(DOD_DYN_ERROR
    > (1.2*DOD_DYN))) %try DOD_DYN_ERROR ~= DOD_DYN(iplus,j_in,k_in)

                DOD_DYN = ((E_d_autonomy(iplus)/3600)+(NOB_1*(
                    max_self_discharge_total_2 + Q_reduction_per_cycle_mean_accum_2
                    )))/(NOB_1*(Batteries_parameters(6,battery_selection_1(j_in)+2)
                    ));%%%%%INCLUDE ERROR LOOP WITH WHILES, must be re-done + (
                    Q_reduction_per_cycle_mean_accum_2(i,j,k)* Full_Q_nominal(1,3*j
                    +k-3)))

                if (DOD_DYN <= 0.4)
                    Q_reduction_per_cycle_mean_2 = 0;
                    Q_reduction_per_cycle_mean_2_1=Q_reduction_per_cycle_mean_2;
                    number_of_cycles_year_1 = number_of_cycles_year_1 + 1;
                else
                    if (0.4 < DOD_DYN) && (DOD_DYN <= 0.6)
                       Q_reduction_per_cycle_mean_2 =
                           Q_reduction_per_cycle_mean_kWh(MMC,3*j_in-2) +
                           ERROR_kWh_cycle(MMC,3*j_in-2);
                       Q_reduction_per_cycle_mean_2_2 =
                           Q_reduction_per_cycle_mean_2;
                       number_of_cycles_year_2 = number_of_cycles_year_2 + 1;
                    else
                        if (0.6 < DOD_DYN) && (DOD_DYN < 0.9)
                        Q_reduction_per_cycle_mean_2 =
                            Q_reduction_per_cycle_mean_kWh(MMC,3*j_in-1) +
                            ERROR_kWh_cycle(MMC,3*j_in-1);
                        Q_reduction_per_cycle_mean_2_3 =
                            Q_reduction_per_cycle_mean_2;
                        number_of_cycles_year_3 = number_of_cycles_year_3 +1;
                        else
                            if 0.9 <= DOD_DYN
                               Q_reduction_per_cycle_mean_2 =
                                   Q_reduction_per_cycle_mean_kWh(MMC,3*j_in) +
                                   ERROR_kWh_cycle(MMC,3*j_in);
                               Q_reduction_per_cycle_mean_2_3 =
                                   Q_reduction_per_cycle_mean_2;
                               number_of_cycles_year_4 = number_of_cycles_year_4+1;
                            end
                        end
                    end
                end

                TMB_replacements_calcul = (Q_reduction_per_cycle_mean_2_1*
                    number_of_cycles_year_1)+(Q_reduction_per_cycle_mean_2_2*
                    number_of_cycles_year_2)+(Q_reduction_per_cycle_mean_2_3*
                    number_of_cycles_year_3)+(Q_reduction_per_cycle_mean_2_4*
                    number_of_cycles_year_4);

                if t_autonomy(iplus+1)==t_m
                    if Q_reduction_per_cycle_mean_accum_2 < max_depth_2
                    Q_reduction_per_cycle_mean_accum_2 =
                        Q_reduction_per_cycle_mean_accum_2 +
                        Q_reduction_per_cycle_mean_2/100;
```

```
                        else
                    Q_reduction_per_cycle_mean_accum_2 = 0;
                    end
                end

               DOD_DYN_ERROR = ((E_d_autonomy(iplus)/3600)+(NOB_1 *(
                   max_self_discharge_total_2 + Q_reduction_per_cycle_mean_accum_2)
                   ))/(NOB_1*(Batteries_parameters(6,battery_selection_1(j_in)+2)))
                   ;

end
               NOB_2 =  (E_d_autonomy(iplus)/3600)/((DOD_DYN*(Batteries_parameters
                   (6,battery_selection_1(j_in)+2))) - max_self_discharge_total_2 -
                    (Q_reduction_per_cycle_mean_accum_2*Full_Q_nominal(1,3*j_in+
                   k_in-3)));
               TBM_Battery_replacement_2 = max_depth_2 / (TMB_replacements_calcul
                   *(1/remain_year));
               max_speed_discharge_2 = Batteries_parameters(13,j_in+2)*NOB_2*
                   Batteries_parameters(4,j_in+2)/Batteries_parameters(14,j_in+2);

E_d_meas_error_accum_autonomy_2 = 0;
E_d_meas_error_accum_2 = 0;


E_d_meas_error_2 = abs(p_d(iplus+1)-p_d(iplus))*(((max_speed_discharge_2*t_m) - abs
    (p_d(iplus+1)-p_d(iplus)))/(2*max_speed_discharge_2));%%INCLUDE ERROR LOOP WITH
     WHILES
E_d_meas_error_accum_2 = E_d_meas_error_accum_2 + E_d_meas_error_2;

                   if t_autonomy(iplus) < SOVProjectdata(21,2)
            E_d_meas_error_accum_autonomy_2 = E_d_meas_error_accum_autonomy_2 +
                E_d_meas_error_2;
                        else
            E_d_meas_error_accum_autonomy_2 = E_d_meas_error_2;
                   end
comp_gain=0.000001;
epsilon_NOB_E_d_meas_error_2 = (E_d_meas_error_accum_autonomy_2/3600 + comp_gain)
    /((DOD_DYN*(Batteries_parameters(6,battery_selection_1(j_in)+2))) -
    max_self_discharge_total_2 - Q_reduction_per_cycle_mean_accum_2);

%rtn_installed_power_nominal(i,j)= NOB(i,j,k)*(Batteries_parameters{6,
    battery_selection_1(j)+2})/(t_autonomy(i)/3600);   %by now just info consider
    to realocate
Maintenance_costs_3_plus(iplus,j_in,k_in) = (SOVProjectdata(51,2) /
    TBM_Battery_replacement_2) * (NOB_2 + (epsilon_NOB_E_d_meas_error_2)) *
    Batteries_parameters(26,battery_selection_1(j_in)+2); %%SIMPLIFIED into
    machinery_blocks_replacement_costs(i,j)
energy_producers_costs_3_plus(iplus,j_in,k_in) = (NOB_1 +
    epsilon_NOB_E_d_meas_error_2) * Batteries_parameters(26,battery_selection_1(
    j_in)+2); %%%CAPEX JUST MODIFY VIA MEASUREMENT ERROR CALCULATION
fuel_costs_3_plus(iplus,j_in,k_in) = ( E_d(iplus) + E_d_meas_error_accum_2 ) /3600
    * Fuel_Cost(2,3) * SOVProjectdata(51,2) / ((t_s(iplus)-t_s(1))/3600*24*365);
        end

    end

end

Maintenance_costs_3(i,j,k) = Maintenance_costs_3_plus(i,j,k);
energy_producers_costs_3(i,j,k) = energy_producers_costs_3_plus(i,j,k);
fuel_costs_3(i,j,k) = fuel_costs_3_plus(i,j,k);
```

```
                end
        end

    else

        if NOBs_feasible_max(j,k) <= Min_max_NOBS(j,k)
            if NOBs_feasible_max(j,k) < NOB_1
Maintenance_costs_3(i,j,k) = 0;
energy_producers_costs_3(i,j,k) = 0;
fuel_costs_3(i,j,k) = 0;
            else
Maintenance_costs_3(i,j,k) = Maintenance_costs(i,j,k);
energy_producers_costs_3(i,j,k) = energy_producers_costs(i,j,k);
fuel_costs_3(i,j,k) = fuel_costs(i,j,k);
            end
        end
    end

        end

    end

end

%%ALREADY CONSTRAINED AND RE-ADJUSTED COSTS

OPEX_2 = fuel_costs_3 + Maintenance_costs_3 ;
CAPEX_2 =  energy_producers_costs_3 ;
TOTAL_COST_2 = OPEX_2 + CAPEX_2 ;
OPEX_per_energy_unit_2 = (OPEX_2./E_d_selection);%no much sense this one
CAPEX_per_energy_unit_2 = (CAPEX_2./E_d_selection);%no much sense this one
TOTAL_COST_per_energy_unit_2 = (TOTAL_COST_2./E_d_selection);%no much sense this one


elapsed = toc;
time2   = clock;
fprintf('TIC TOC: %g\n', elapsed);
fprintf('CPUTIME: %g\n', fintime - initime);
fprintf('CLOCK:   %g\n', etime(time2, time1));
```

D Publications

Here is attached the pdf. document with the conference paper related to the present project published in ITEC2021 called "*Integrated Design and Control Approach for Marine Power Systems Based On Operational Data; 'Digital Twin to Design'*".

Integrated Design and Control Approach for Marine Power Systems Based On Operational Data; "Digital Twin to Design"

Dalia Casanova Mombiela
Norwegian University of
Science and Technology (NTNU)
Marine Technology Centre
Trondheim, Norway
Email: daliac@stud.ntnu.no

Mehdi Zadeh
Norwegian University of
Science and Technology (NTNU)
Marine Technology Centre
Trondheim, Norway
Email: mehdi.zadeh@ntnu.no

***Abstract*—This paper proposes an algorithm to design ship power systems in the preliminary design phase. As a case study, an embedded control is integrated into the preliminary design of the ship power system, at the level of Energy Management System (EMS). The embedded control developed for the algorithm aims for cost, availability, safety and emissions optimization from the top layer. At the power system level, a few alternatives are considered such as full electric propulsion and fuel-based energy producers. Different Key Performance Indicators (KPIs), Key Exception Indicators (KEIs) and Key Improvement Indicators (KIIs) for design are evaluated for cost optimization purposes. Power plant sizing results of an Offshore Supply Vessel based on batteries or Generating Sets (GENSETs) power contribution are extracted with the proposed pro-clean power plant design algorithm structure. The result of this first simplified simulation not just include a comparative evaluation between 7 different types of batteries for an all electric ship sizing but also a maximum and instantaneous Depth of Discharge (DoD) of the batteries among the OSV load profile register which could be used as a control bandwidth to consider at the EMS level. The presented algorithm structure is a preface for later hybrid systems power plant sizing generalization.**

I. Introduction

Consequent to the increasing developments in marine electrification [1], [2], and alternative marine fuels [3], the design of the on board power systems has been a crucial issue to meet the ship mission and operational requirements, e.g., total power demand, while evaluating KPIs and design optimization variables, such as reduced costs or emissions. However, the existing systems design guidelines for ships are not yet mature and they are usually based on minimum safety ranges, translated into challenging implementation for systems optimization goals. However, the on board systems control settings and load profile have significant effect on an optimum design of the power system. Hence, a first step to optimize the design results is to consider the system performance under operation, using real systems data storage properly scaled up or processing data from specific system configurations under research such as the one in [4].

From the marine power systems engineering perspective, system level design methodologies influence the interest of ship designers and operators such as digital twins [5] or data driven models [6] in-line with systems model reduction approaches for the analysis and development of dynamic low level control presented in [7] and more recent research [8] with model reduction approaches for power systems performance evaluation. Nowadays, digital twins are a target for research and development for full-system simulations for prototyping, verification, training and performance studies. An example of open virtual prototyping framework for maritime systems and operations is presented in [10]. Digital twins can face up to include different modules of design for a wide range of different components of the ship. The commercial definition of digital twin as a sophisticated platform with the capability of real-time simulation does not well fit for a preliminary ship design, as it is defined in the maritime industry [11]. From the control engineering or maintenance engineering disciplines, these methods, which could simulate the system in real time either offline or online [12] for specific case studies, well fit for controllers design new era on board [13] and maintenance strategies improvement, such as the demanding implementation of Reliability Centered Maintenance [14] in the maritime sector.

Nevertheless, shipyards and technical offices are required to individually develop its own procedures of calculus for each new project to scope a first proper solution of the ship power plant. These procedures are interesting to be re-structured in a standardized tool with a generic core algorithm which includes the natural flow that design engineers would follow each new project. Feasibility and optimization should hold a proper structure which integrates, via data input, the nature of the project, the ship type environment constraints and the correspondent client wishes in a potential new concept called "Digital Twin to Design".

The closest structure to the proposed "Digital Twin to Design" approach include different EMS developments with deeper system behaviour studies integrating machine learning techniques, e.g., [15] for vessels having cyclic operations, or the ongoing research around fuel consumption reduction by installing storage elements which requires of power management strategies to evaluate its optimization [16]. Nevertheless, this work re-structures the procedure of calculus where a robust core is aimed to be used and further improved each case study of analysis. The main outcome of the algorithm changes from a real time conditioned operation signals tight to a specific case study to a problem formulation focused on the preliminary design phase accuracy which first cares about the power plant external design links to scope a feasible scenario of solutions with its correspondent optimum operational bandwidths.

Inside the ship design process the work development focuses on the power system design for several reasons. First, a high probability to find a pattern to optimize the combination and sizing of components inside a power system design process. Another reason is the big number of emerging new technologies in the maritime sector currently available to be installed on board, e.g., batteries, fuel cells, prime movers driven by alternative fuels or emissions reduction technologies, such as scrubbers or the ongoing research around decarbonization techniques. DNV analyses the existing scenario and future trends for energy generation on board in [18]. Non of them are considered, by now, as a unique alternative to meet the Paris Agreement upcoming goals but all of them could contribute in a proper combination each new project to comply with the increasingly tight environmental regulations constraints, guided by the Kyoto protocol, for Green House Gas (GHG) emissions and the Paris Agreement with CO_2 reduction purposes. These agreements and future international goals compliance are controlled by the regulatory authorities as the International Maritime Organization, U.S. Environmental Protection Agency or the European Commission and the consequent Regional Governments guidelines with shorten time challenging goals proposed to be achieved together with the industry efforts.

The main objective of this work is to develop an optimized design tool to be compatible with a ship control design bandwidth for real operation which ensures optimum power plant performance. To achieve this, the control variables, at the EMS level, are embedded in the design platform to emulate the behaviour of the power system. Based on the developed platform, in future steps, a control methodology or proof of compliance under specific conditions can be adopted to introduce a control constrained environment. Then, using an optimization procedure, a proper selection of an optimum pro-clean energy generation solution is aimed. Each module of the algorithm development is presented here together with the core structure settings of the algorithm applied to the retrofit project of an Offshore Supply Vessel for first results analysis. The algorithm and its standardization potential will grow up by including the design requirements for different case studies. The main purpose is to keep the algorithm robust and flexible by generalizing the core steps of the design process and defining a clear environment of real data inclusion and processing, useful for different environments.

II. Methodology of Integrated Design and Control

Figure 1 illustrates the overall concept, input and output environments, and the top-level structure of the algorithm. The aim of the proposed platform is to keep the core algorithm flexible to fit with different case studies which is achieved via thoughtful data input structure organization and power plant design generic pattern identification. Operational conditions, project nature and the state of the art of the power system components market are assessed in 3 different input packages, where a proper load profile estimation plays the main role to introduce a real operational environment for analysis. Rules and regulations translated into constraints data and a Relational Data Table linking the whole ship design with the specific power plant assessment, are introduced for further data processing. To simplify the evaluation and to evaluate among lower computational times it is required to first well filter the market state of the art confronting the operational profile data with project nature data input. Feasibility and optimization assessments define the core of the evaluation with the purpose of tightening the optimization scenario to the feasible combinations. Weight, space and autonomy feasibility constraints establish the link with the external ship design. Power instantaneous estimated response of the power system solution studied each step closes the feasibility assessment to get a first scope of solutions, input to the optimization environment.

The output environment of the evaluation process includes a clear structure definition for the available open source data and the required additional data from interested parties, e.g., specific measurements on board for a retrofit evaluation. From the Digital Twin to Design environment, the targeted output includes a scope of optimum solutions, defined in energy producers number, size and operational bandwidths among the introduced load profile. At the same time KPIs, KEIs and KIIs are defined for the power plant design process to evaluate the impact on operational bandwidths change from the optimum ones during the ship life cycle. These data could be introduced into a digital twin or data driven model of one of the optimum combos from the existing feasible scenarios, updated at any time by a data base. In the low level systems performance testing the output is translated into Energy Management System operational bandwidths to be tested for stability and control at the Power Management System level and control settings. The output of the low level evaluation (e.g., digital twins) feeds back the Digital Twin to Design with further constraints in control feasibility and robustness among the tested scenarios also including detailed maintenance evaluation of the selected case studies for testing safety levels and the accuracy of maintenance costs output.

A. *Algorithm structure*

The present algorithm looks for sizing optimization. The components size is estimated from a minimum load response perspective which becomes feasible for the project introduced for study.

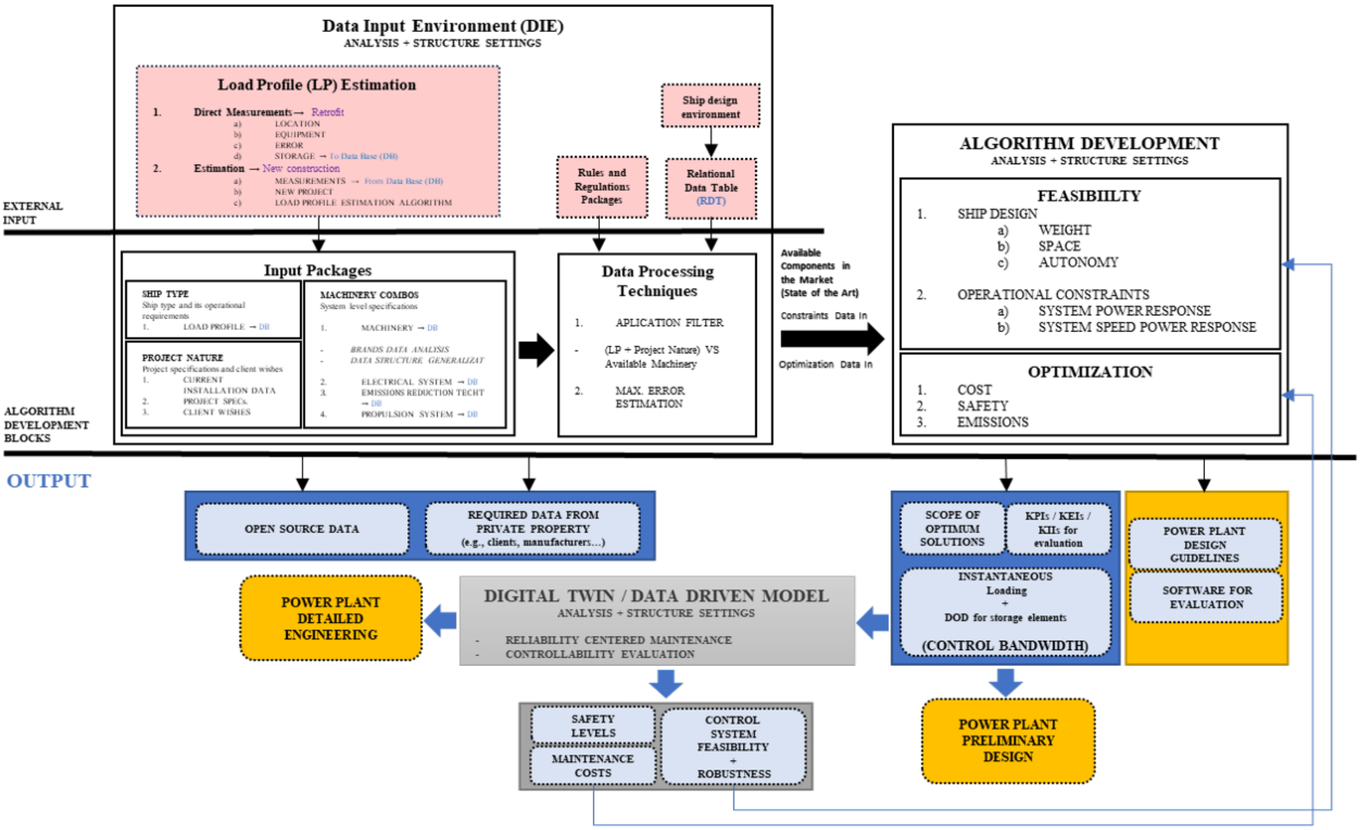

Fig. 1. Overall Project Structure.

The algorithm uses MATLAB code with a mixed integer programming core, following the proposed single variable unconstrained optimization function in 1, obtained from a constrained design environment, called here Optimization Constrained Matrix (OCM), as the front hold of the evaluation structure, simplified each case study following specific systems design natural flow and establishing comparative evaluation.

$$OCM = min\left(c_{TC_{jkp}}\right) = min\left(\sum_{i\in I} c_{TC_{ijkp}}\right) \tag{1}$$

Where the specific total costs matrix is given by:

$$c_{TC_{ijkp}} = \left(\frac{C_{Tijkp}}{E_{i_{acc}}} \times CM_{ijkp}\right) \tag{2}$$

$$CM_{ijkp} = CM_{ij} \times CM_{jk} \times CM_{jp} \tag{3}$$

s.t.
i = number of load measurements $\forall i \in I$
I = load measurements set
j = power source type number, from a data base list charged $\forall j \in J$
J = power sources set
k = machinery loading slots as % of the total load demand $\forall k \in K$
K = feasible loading set, each machinery type
p = fuel type number $\forall p \in P$
P = fuel type set
E = Instantaneous energy measured each time step i.
CM = Constraints Matrix $\forall\ cm_{ijkp} \in [0, 1]$

TABLE I
FEASIBILITY ENVIRONMENT.

Constraints	Units	Intervening parameters	Options	Mode	Intervening packages
Ship Design Feasibility					
Autonomy	years	E_d_acum	Fix	FEM	Ship type (LP)
		t_autonomy	Fix	FEM	Project Nature (PSPCs)
		E_d_acum	Variable	FFHM	Ship type (LP)
		t_autonomy	Variable	FFHM	internal variables
Weight	kg	max. Installation Weight	Fix	FEM/FFHM	Project Nature (min(PSPCs,CW))
			Max. Speed detriment	FEM/FFHM	Relational Data Table
Space	m	machinery room Length	Fix	FEM/FFHM	Project Nature (PSPCs)
	m	machinery room Width	Fix	FEM/FFHM	Project Nature (PSPCs)
		machinery room Height	Fix	FEM/FFHM	Project Nature (PSPCs)
		min. Length margin	Fix	FEM/FFHM	Project Nature (PSPCs)
		min. Width margin	Fix	FEM/FFHM	Project Nature (PSPCs)
		min. Height margin	Fix	FEM/FFHM	Project Nature (PSPCs)
		B. orientation (St-Bw;Pt-Sb)	Fix	FEM	Project Nature (PSPCs)
		% B	Fix	FFHM	Project Nature (PSPCs)
Operational Feasibility 1					
Max. Inst. Speed	$\Delta kW/\Delta t$	E_d_acum	Fix	FEM/FFHM	Ship type (LP)
		t_R_machinery	Fix	FEM/FFHM	Machinery Combos (MCO)
Operational Feasibility 2					
Max. Power drop	ΔkW	power_drop	Fix	FEM/FFHM	Ship type (LP)
		t_m	Fix	FEM/FFHM	Ship type (LP)

Feasibility around weight, space and autonomy followed by cost optimization is proposed for evaluation at this step aiming energy producers sizing for a specific maximum Depth Of Discharge (DoD), estimated for storage elements, or loading factor estimation, for rotatory machinery, among the introduced OSV load profile. Electrical systems, emissions reduction technologies and a multi-objective optimization environment with safety and emissions levels remains open for later studies and a proper inclusion.

- **Optimization:** Figure 2 illustrates the holding costs contribution to apply every new case study where each box

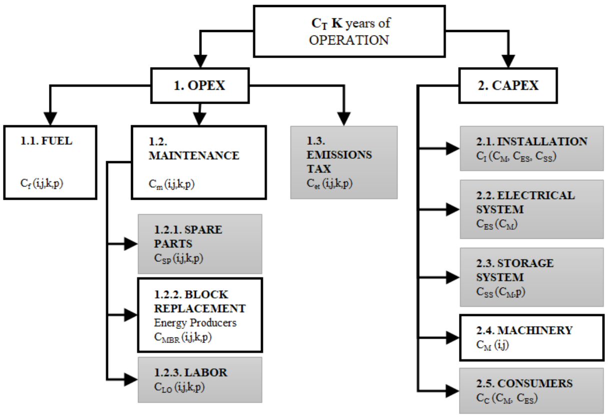

Fig. 2. Power and Propulsion Plant Costs Contribution.

will be re-defined under analysis requirements. All white boxes are inserted for the present evaluation.

- **Feasibility:** Table I illustrates the feasibility environment broken down into ship design constraints and operational constraints introduced at different steps of the evaluation. All these parameters are compared, inside the algorithm, to the machinery data introduced with the correspondent package in Figure 1 via dimensional variable, Number Of Elements (NOE) and renamed each new source of power inserted into the algorithm, e.g., Number Of Batteries (NOB) for batteries sizing analysis.

B. *Assumptions*

1) If the instantaneous power-speed response of the battery bank by design complies with the ship load requirements the system is considered controllable in hardware level, e.i. feasible power response, voltage control, frequency control, etc. The algorithm is tight to the assumption by now before researching on proof of compliance.
2) A battery module connected by several cells in parallel could be considered as a single cell with high capacity. Hence the SoC, (1-DoD), could be estimated like a single cell (due to the self-balancing characteristic of the parallel connection), [9].
3) A minimum DoD of 50% the nominal capacity, Q, is considered to produce Q detriment per cycle.
4) All storage elements are considered initialized at 100% of charge at the first load profile step registered and introduced in the algorithm. The minimum autonomy of the power system, with no re-charge, should be set based on harbor stop intervals where the storage system is considered to be fully re-charged.

III. Case Study

An Offshore Supply Vessel is presented for study. All data introduced is accurate enough for this simplified evaluation carried out for comparative purposes. Table II illustrates the assigned class notations by DNV to the present case study which define the project environment. The vessel is around 80 meters LOA and 18 meters beam, with a dead weight of around 4.000 tonnes and a maximum speed by design of 15,8 knots.

TABLE II
DNV Class Assigned to the OSV.

Main Cass Notation		1A	
Ship Type		Offshore Service Vessel Supply	
Strengthened	DK	**LFL**	2
HL	2.8	**OILREC**	OILREC
Battery	Safety	**ICE**	C
E0		**CLEAN**	Design
DYNPOS	AUTR	**COMF**	V-3
NAUT	OSV(A)		

Considering the load profile measured at the output each GENSET and the correspondent rated power by design, Table III represents the loading of the 4 machines over 44 days of measurements registered. The numbers represent how one of the GENSETs, G1, is likely under the role of "swinging machine" by suffering the current back flows with expected higher maintenance costs in a medium term perspective. In 44 days G1 accumulates up to 1556 kWh of reversed energy interesting to be re-used in future research analysis. The 4 installed GENSETs work non-stop among the whole sampling period, however, they run most of the time at very low loading conditions of less than 22% of the Maximum Continuous Rating (MRC) each.

TABLE III
GENSETs Loading and Reversed Energy Measured

LLO	22	% MCR					
MCR	assumed =	P_rated					
Ranges	**0≤%<LLO**	**LLO-60%**	**60%-80%**	**80%-90%**	**>90%**	**Reversed Power**	**Reversed Energy**
	[%]	**[%]**	**[%]**	**[%]**	**[%]**	**[%]**	**[kWh]**
G1	11,385 %	3,786 %	10,104 %	0,851 %	0,002 %	**74,799 %**	**1556**
G2	60,654 %	32,166 %	7,294 %	0,371 %	0,012 %	**0,000 %**	**0,272**
G3	59,936 %	33,882 %	3,665 %	2,574 %	0,009 %	**0,063 %**	**0,717**
G4	86,095 %	6,134 %	8,292 %	0,108 %	0,006 %	**0,000 %**	**0**
TOTAL	54,517 %	18,992 %	6,792 %	0,976 %	0,007 %	**18,716 %**	**1556,989**

A. *Full Electric Mode (FEM)*

The present mode, just considering batteries as a main source of power, requires from two loops to be computed among the load profile registered or an specific feasible time slot of it, extracted from the feasibility environment in Table I. Seven lithium batteries with different application and sizes, with the correspondent technical data sheet are proposed for evaluation and summarized in Table IV.

TABLE IV
Batteries Specifications

	Battery TAG	**Bat**		**RelLIH1**	**RelLIH2**	**RelLIH3**	**RelLIC1**	**RelLIC2**	**RelLIC3**	**RelLIC4**
SCOPE 1	**Cold weather**	**CW**		0.00	0.00	0.00	1.00	1.00	1.00	1.00
	Chemistry	**CH**		Li	Li	Li	Li	Li	Li	Li
SCOPE 2	**Nominal Voltage**	V_N	**V**	12.80	12.80	12.80	12.80	12.80	12.80	12.80
	Nominal Capacity	Q_N	**Ah**	50.00	100.00	300.00	20.00	50.00	100.00	300.00
	Max. Self Disch./month	**max.SD**	**%**	3.00	3.00	3.00	3.00	3.00	3.00	3.00
	Cost	**C**	**€**	528.96	1091.06	3033.20	275.63	558.76	1116.73	3279.07
	Weight	**Wt**	**kg**	8.50	13.50	37.50	3.00	6.38	12.64	34.54
	Lenght	**L**	**m**	0.26	0.33	0.52	0.18	0.20	0.33	0.52
	Width	**W**	**m**	0.17	0.17	0.27	0.08	0.17	0.17	0.27
	Depth	**D**	**m**	0.22	0.22	0.23	0.17	0.17	0.22	0.23
SCOPE 3	**Max. peak discharge I**	$I_{PD_{max}}$	**A**	400.00	800.00	800.00	40.00	100.00	200.00	200.00
	Peak discharge I time	$t_{PD_{min}}$	**s**	3.00	2.00	2.00	7.50	7.50	7.50	7.50

1^{st} **loop, size adjustment:** NOBs required to cover the accumulated energy at 3 different maximum DoD, 0.5, 0.8 and 1, calculated among the SOV load profile introduced. The number of batteries required and the costs of under operation considered from Figure 2 are evaluated for accumulated energy values constrained and recover for a minimum autonomy slots specified by the designer/engineer. Self Discharge (SD) per month and nominal capacity detriment per cycle $(Q_{N\,dcyl})$, which integrates a maximum computing error estimation, are included in the calculation from open source batteries data sheets. The main intervening feasibility and optimization calculus are held by equations 4 and 5.

$$NOB(i,j,k) = \frac{E_{aut_{acc}}(i)}{(DOD_{max}(k)\times Q_N(j)) - SD(j,time) - \left(Q_{N_{dcyl}(i,j,k)}+\epsilon\right)_{acc}} \tag{4}$$

$$C_T(i,j,k) = OPEX + CAPEX \tag{5}$$

s.t.,

$$OPEX(i,j,k) = \left(\frac{E_{aut_{acc}}\times c_f}{t(n)-t(1)} + \frac{NOB\times C_B\times Q_{N_{dcyl}}\times(t(n)-t(1))}{(1-\%_{max_d})\times\sum t_{aut}==tm}\right)\times K \tag{6}$$

$$CAPEX(i,j,k) = NOB \times C_B \tag{7}$$

Being K the number of expected life of the ship in years, included inside Project Nature input package from Figure 1; $\%_{max_d}$ the assumed depth of the battery at a 30% of detriment from its Q_N; and c_f electricity costs when charging from the network. Costs calculation is elaborated considering fixed minimum autonomy settings, which means no recharge available during this period, and repeating the ship operational load profile among the expected remaining life of the ship. For the presented estimation battery block replacement is included as maintenance costs when the battery is assumed dead due to self discharge influence and capacity detriment per cycle as a function of DoD.

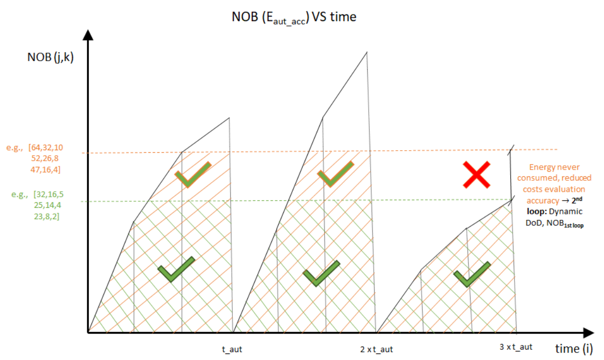

Fig. 3. Conceptualization of the FEM Evaluation Environment.

2^{nd} **loop, costs evaluation accuracy improvement:** Once a first sizing is estimated to cover the required energy demand between recharge times, a dynamic DoD must be estimated for the already calculated NOBs which are not going to use its full capacity during some of the specified minimum autonomy slots, as it is conceptualized in Figure 3, with the consequent maintenance costs reduction as battery pack replacement in this example. Hence, new costs calculation is implemented for further accuracy at that sizing requirements. Computational time for the calculation can be further reduced by applying the ship design constraints environment to the first calculated NOBs. While the costs calculus validation becomes stronger for autonomy time slots with smaller total energy demand, the feasibility environment, explained at the beginning of Section II-A, is expected to exclude higher battery sizes. As a consequence, by selecting properly the desired autonomy for study, the remaining scope of NOBs' dynamical DoD calculation among the load profile is reduced from OPEX costs. The formulation in equation 8 is inverted this loop from equation 4 with the correspondent estimated capacity detriment per cycle readjustment in the code.

$$DOD_{dyn}(i^*,j,k) = \frac{E_{aut_{acc}}(i^*) + NOB(i,j,k)\left(\left(Q_{N_{dcyl}}(i^*,j,k)+\epsilon\right)_{acc} + SD(j,time)\right)}{NOB(i,j,k)\times Q_N(j)} \tag{8}$$

Then $\forall(i,j,k)$ where

$$min(NOB_{max}/cycle) < NOB < (NOB)_{feasible} \tag{9}$$

the correspondent $NOB(DoD_{dyn})$ calculus to re-calculate maintenance costs is shown in equation 10.

$$NOB_2(i^*,j,k) = \frac{E_{aut_{acc}}}{(DOD_{dyn}(i^*,j,k)\times Q_N) - SD - \left(Q_{N_{dcyl}}+\epsilon\right)_{acc}} \tag{10}$$

The present formulation is thought to be a baseline for a later energy share optimization analysis of a hybrid power and propulsion system solution.

B. Fossil Fuels Mode, FFM

The currently installed power system runs with Catepillar GENSETs which embedded engines are recommended to be driven by Heavy Fuel Oil with Low Heating Values of around 42,780 kJ/kg, [19], and an estimated fuel cost of around 416 \$/mt (0,36€/l) if considering IFO380 marine fuel commonly used, [20].

Fuel consumption curves extracted from C280-8 and 3508B GENSETs, models of Caterpillar catalog with a maximum rated power of 2420 ekW and 910 ekW respectively, are considered. From the simplified fuel costs calculation in equation 11 together with the data included in Table III a result of the expected fuel costs in the following 30 years of the vessel is shown in estimation 12.

$$C_{FK} = \left(\sum_{j=1}^{n}\sum_{k=1}^{m} h_{Tj} \times \frac{perc_{jk}}{100} \times sfc_{jk} \times c_f\right) \times \frac{K}{t_s} \tag{11}$$

s.t.

j = Genstets number $\forall j \in N \wedge 1 \leq j \leq$
n = max. number of Gensets. n = 4 for this case study
k = Gensets loading slots $\forall k \in N \wedge 1 \leq j \leq m$
m = max. number of Gensets loading slots
$perc_{jk}$ = % of the total running hours each i & j
sfc_{jk} = specific fuel consumption each i & j
h_{Tj} = running hours, each i
c_f = specific fuel cost
K = expected ship life, time left for the retrofit case
t_s = load profile time registered
Table III defines the loading slots for this case study.

$$C_{F30} \approx \$63.862M \approx 63,28MEUR \tag{12}$$

The presented case study shows interesting points of improvement and analysis within the power plant design appealing for a better power generation and distribution system efficiency, overall emissions reduction and load sharing control strategies implementation to tackle the analysis, together with additional technologies proposal and retrofit projects evaluation.

IV. Results discussion

Project data input selection for simulation is included in Table V and the reduced load profile slot selected from 5 days register of the present case study is shown in Figure 4 including the most demanding time slot in terms of instantaneous power demand. Three to seven batteries are excluded in the first application filter due to operation specifications under low temperature conditions.

TABLE V
SHIP DESIGN INDEXES

	Value	Units	Data in Accuracy
Minimum temp. working condition	-20	Co	low
Min. autonomy (time)	**3600**	**s**	low
Min. max. design speed	15	kn	high
Machinery Room Length	25.02	m	low
Machinery Room Width	12.6	m	low
Machinery Room Depth	2.676	m	low
L "safety and add" installations marging	0.4		low
W "safety and add" installations marging	0.2		low
D "safety and add" installations marging	0.2		low
Max. weight expected from machinery	500000	kg	
BAT_Li placement distribution	**1**	**1/2**	
Total Installed power	7256.34	kW	

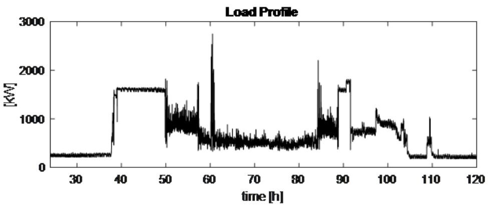

Fig. 4. Load Profile for simulation.

A. Feasibility

Table I includes the results obtained from the feasibility evaluation under the Project Data Input selection in Table V. On one side, weight and space constraints are conflicting the feasibility of the design for minimum autonomy requirements of 1 and 3 days when trying to adjust batteries to cover the total load demand with the correspondent increment in volume and weight of the battery pack. On the other side, lower autonomy aims for smaller battery packs which deals with slower operational responses.

For the present case study, time between re-charges of 1h and less allows to adjust a battery pack size to comply with space and weight project constraints for the four batteries under analysis with different sizes. Nevertheless, less than one hour settings of minimum required autonomy conflicts with the instantaneous power demand in terms of system speed response for batteries with nominal capacity of 300 Ah, the bigger ones, meaning that, for the same energy response, smaller batteries in higher number of them could give faster responses than bigger batteries in lower number conforming the battery pack. This time, maximum DoD for design, code indexed by k, does not cause any conflict in the feasibility environment.

Feasible solutions are identify in Table VI. NOBs required each feasible solution are included in Table VII and later used as $(NOB)_{feasible}(j,k)$ bandwidths applied to the inequality 9.

TABLE VI
FEASIBILITY ENVIRONMENT

Autonomy [s]	k/j	Weight B1	Weight B2	Weight B3	Weight B4	Space B1	Space B2	Space B3	Space B4	Operation_1 B1	Operation_1 B2	Operation_1 B3	Operation_1 B4
	0.5	1	1	1	1	1	1	1	1	1	1	1	0
1800	0.8	1	1	1	1	1	1	1	1	1	1	1	0
	1	1	1	1	1	1	1	1	1	1	1	1	0
	0.5	1	1	1	1	1	1	1	1	1	1	1	1
3600	0.8	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	1
	0.5	0	0	0	0	0	0	0	0	1	1	1	1
86400	0.8	0	0	0	0	0	0	0	0	1	1	1	1
	1	0	0	0	0	0	0	0	0	1	1	1	1
	0.5	0	0	0	0	0	0	0	0	1	1	1	1
259200	0.8	0	0	0	0	0	0	0	0	1	1	1	1
	1	0	0	0	0	0	0	0	0	1	1	1	1

TABLE VII
REQUIRED NOBS(J,K)

Autonomy [s]	k/j	*NOB(k,j)* B1	B2	B3	B4
	0.5	7600	3040	1520	507
1800	0.8	4750	1900	950	317
	1	3800	1520	760	254
	0.5	14328	5731	2866	956
3600	0.8	8955	3582	1791	597
	1	7164	2866	1433	478

B. FEM costs evaluation

To evaluate costs among each machinery combination, for the FEM translated into battery pack sizing, indexes evaluation, $\sum_i c_{jk}$, are used for comparative purposes and real costs value output can be also considered if the costs function is completed properly with accurate enough data input.

To test the algorithm first and second loop outputs Figure 5 illustrates the summary of specific accumulated costs of each load profile step, each battery and DOD_{max} limit proposed for design. Batteries of 50 Ah claim for higher specific costs from both CAPEX and OPEX, as they are define for this first simplification. By including the summary of specific costs as an index for comparative evaluation the load profile nature is deeply considered. From this first loop a DOD_{max} for design of 50% is costly for specific CAPEX and cheaper for specific OPEX than $DODs$ of 80% or 100%. However, as exemplified also in Figure 9 OPEX reflects the strongest influence for a FEM of battery power generation due to high maintenance resulting cost from battery pack replacement among time under the present assumptions.

Then, specific costs summary is extracted from the second loop, where costs estimation is re-adjusted. This time Figure 6 fixes a DOD_{max} of 50% and identifies as the best solution a battery individual size of 300 Ah, the cheapest solution for the given load profile sample. Nevertheless, the difference between the 3 biggest batteries is not as meaningful as the costs increment for the smallest one, following the trend extracted from the first loop. For comparative purposes a first loop could be enough, waiting for further case studies tests, but the value for the summary of specific costs is reduced, claiming for

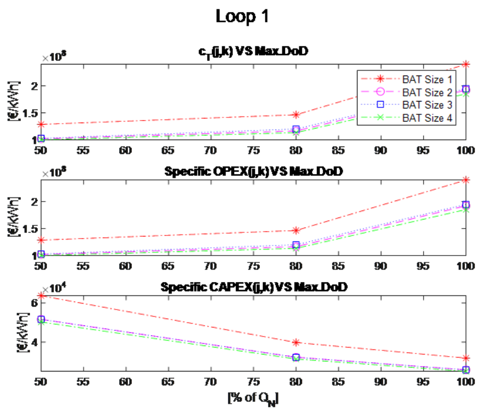

Fig. 5. Summary of specific costs each battery at different DOD_{max} for the whole load profile sample, Loop 1 results extraction.

the second loop-readjustment when they are under evaluation. Once $DOD_{max} = 50\%$ is fixed, Figures 7 and 8 illustrate

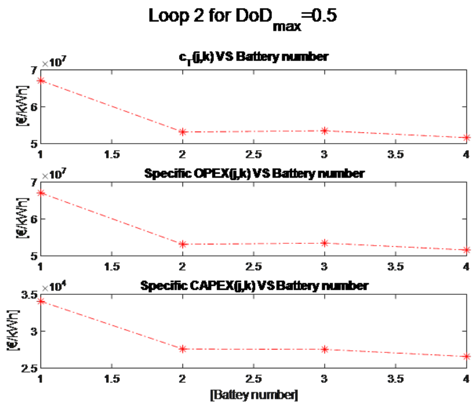

Fig. 6. Summary of specific costs each battery at $DOD_{max} = 0.5$ for the whole load profile sample.

specific total costs among time reflecting how the battery pack is more profitable over time disregard-less of battery pack replacement costs influence. It is important to notice that costs calculation each time step is done for the predefined K years of expected ship life repeating the inserted load sample over that time. Regarding output accuracy, the plots reflect the need for a second loop re-adjustment. Selected data input

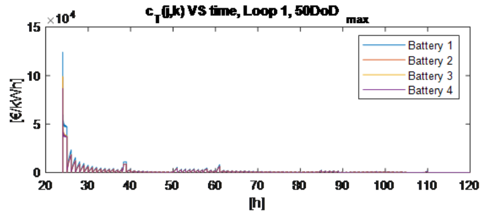

Fig. 7. Specific costs each battery at $DOD_{max} = 0.5$ for the whole load profile sample, Loop 1.

and minimum autonomy settings for a DOD_{max} of 50% are considered feasible along the whole load profile, hence no 0 values output in Figure 2 are expected. These values are the output of loop 2 and, zooming them in Figure 10 for a load profile up to around 90 hours with the inserted pattern the costs for the expected life of the ship is reduced. In contrast with it, if the load profile pattern is consider up to around 60 h the inserted one, this total costs will increase. Total costs results are dependent on time line position, which means becoming more accurate to the real output costs from ship operation among time with a correct estimation of the load pattern.

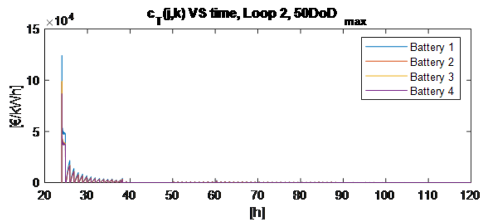

Fig. 8. Specific costs each battery at $DOD_{max} = 0.5$ for the whole load profile sample, Loop 2.

Finally, total costs are extracted

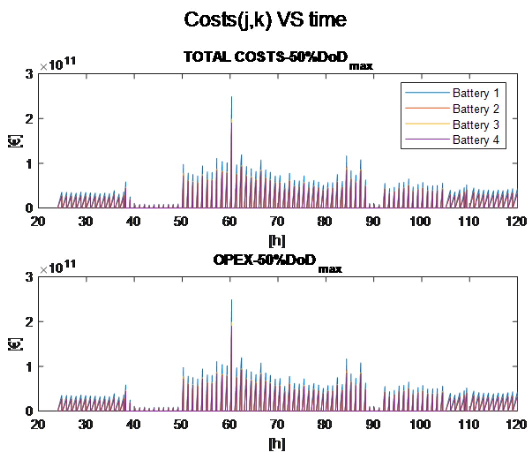

Fig. 9. Total Costs, $DOD_{max} = 0.5$ each battery size

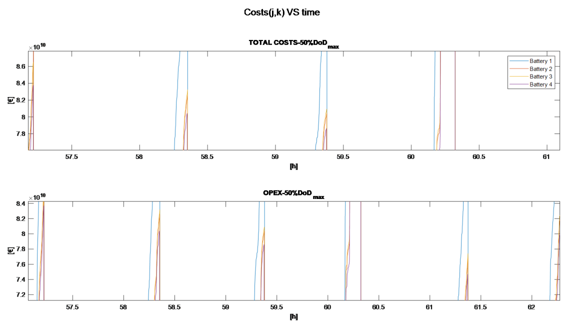

Fig. 10. Total Costs zoom, $DOD_{max} = 0.5$ each battery size

V. Conclusion

In this paper, an integrated design and control algorithm is presented and tested applicable to the preliminary design of ship hybrid power systems. Here, the control design is at the level of energy management and with the possibility for cost optimization. At the power system level, a few alternatives are tested such as full electric propulsion and fuel-based propulsion. The design is then evaluated together with the defined indices such as KPIs, KEIs and KIIs mentioned in VIII. A case study is tested with the data collected from an Offshore Supply Vessel. The results show the importance of a proper battery detriment under operation, just able to be well identify with an accurate enough load profile estimation claiming from real data storage and processing from existing vessels energy production or well define power systems mathematical models for testing. The estimated load profile should identify a recurrent power demand pattern which, if introduced in the algorithm, will give a proper costs result for evaluation.

From this structure settings, the algorithm is ready to get stronger with additional real data input inclusion increasing also costs function sections as defined in Figure 2 and adding at the end a multi objective optimization environment including safety and emissions with the corresponding waiting factors.

For the whole sample batteries performance at a maximum DOD of 50% the installation is optimized in costs with an individual battery capacity of 300 Ah required in a number of 956 batteries for the ship specifications limits in Table V. The battery pack needs to be recharged each hour to perform under operational requirements. This environment has been selected to test the algorithm, however, for a real output accurate evaluation the whole load profile insertion and an acceptable minimum autonomy should be integrated. From this previous result a FEM for the specific ship would not be feasible and the hybrid mode will be the next step for evaluation due to the small time between re-charges (minimum autonomy) required for feasibility compliance.

Considering the difference between fuel costs expected from FFM, without maintenance costs inclusion, and FEM with battery pack replacement due to nominal capacity detriment inclusion in the costs function, a battery pack installation is not optimum and it requires for further support from fossil fuels sources to become feasible due to the small time between re-charges requirement. Nevertheless, emissions reduction and safety must be included and weighted versus costs optimization.

TABLE VIII
OSV-FEM, KPIs/KEIs/KIIs of Interest

		IDEXES TAG	CHECK
KPIs		c_{TCijkp}	minimum (i,j)
KEIs	Accuracy	DoD_{dyn}	0 <DoD <1
		$Q_{reduction/cycl}$	$0 < Q_{r/cycl} < Q_N$
KIIs	Estimation	ϵ_{Eaccum}	$\epsilon_{Eaccum} < E_{accum}$
		$\epsilon_{Qr/cycl}$	$\epsilon_{Qr/cycl} < Q_{r/cycl}$
		Load profile	Expected deviation
	Computational time	CPUTIME	
		CLOCK	

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