PROCEEDINGS OF ECOS 2023 - THE 36TH INTERNATIONAL CONFERENCE ON
EFFICIENCY, COST, OPTIMIZATION, SIMULATION AND ENVIRONMENTAL IMPACT OF ENERGY SYSTEMS
25-30 JUNE, 2023, LAS PALMAS DE GRAN CANARIA, SPAIN

Application of genetic algorithms to the design and dimensioning of maritime hybrid power plants fueled by alternative fuels

Álvaro Benet[a], Antonio Villalba-Herreros[a,b], Óscar Santiago[a,b] and Teresa J. Leo[a,b]

a Universidad Politécnica de Madrid, Madrid, Spain,
b Grupo de Investigación UPM Pilas de Combustible, Tecnología del Hidrógeno y Motores Alternativos (PICOHIMA), Madrid, Spain, teresa.leo.mena@upm.es,

Abstract:

The combination of emerging technologies such as fuel cells with well-known internal combustion engines, gas turbines and/or batteries is expected to enhance the efficiency of the resulting hybridized power plants compared to conventional ones installed onboard ships. Besides, the use of alternative fuels such as hydrogen, methanol or ammonia to power ships will allow to reduce the carbon footprint of vessels. However, hybridization and the use of alternative fuels imply that several variables such as efficiency, reliability, flexibility, space requirements, mass, investment costs or maintenance costs need to be taken into account simultaneously. To approach these designs Genetic Algorithms can be helpful. Genetic Algorithms are a powerful tool for solving a wide range of optimization problems in which several variables play a key role on the performance of the solution demanding a trade-off solution that also considers conflictive phenomena between these variables. In this work, the application of Genetic Algorithms to the design of hybridized marine power plants aiming to find compromised solutions is described. The outcome of these applications will help in the decision-making process to select the different components within the power plant, as well as the dimensioning of their capacities to get the most suitable design in accordance with a defined set of requirements that must be met.

Keywords:

Multi-objective optimization; Genetic algorithm; Hybrid power plant; Alternative fuels; Maritime.

https://doi.org/10.52202/069564-0088

1 Introduction

Multi-objective optimization problems (MOPs) arise frequently in engineering applications where several objectives need to be optimized simultaneously. In such cases, optimization algorithms are commonly used to solve that MOPs due to their ability to handle multiple criteria and objectives and search for the solution space efficiently. In the present work, the methodology for the application of an optimization algorithm on the design of a marine hybrid power plant is presented. This methodology will allow to create a tool to help in the decision-making process of the different power generation components of a marine hybrid power plant.

In Section 2, a brief review about the state-of-the-art of multi-objective optimization algorithms applied to power plant generation problems is presented. Non-Dominated Genetic Algorithm II (NSGA-II), Particle Swarm Optimization (PSO) and Strength Pareto Evolutionary Algorithm II (SPEA II) are found among the most used algorithms used for power plant generation problems. Economics, emissions and efficiency are found as the main objective functions defined.

The combination of emerging technologies such as fuel cells with well-known internal combustion engines, gas turbines and/or batteries is expected to enhance the efficiency of the resulting hybridized power plants compared to conventional ones installed onboard ships. Besides, the use of alternative fuels such as hydrogen, methanol or ammonia to power ships will allow to reduce the carbon footprint of vessels. However, hybridization and the use of alternative fuels imply that several variables such as efficiency, reliability, flexibility, space requirements, mass, investment costs or maintenance costs need to be taken into account simultaneously. All this results in a problem with multiple inputs, multiple variables well as multiple goals to fulfil simultaneously. Multi-objective algorithms are a powerful tool to cope with this problem. Nevertheless, a case-specific methodology adapted to the problematic of a modern marine hybrid power plant from needs to be developed to allow the use of multi-objective algorithms. In Section 3, this methodology is explained. Key aspects and future works to the methodology are discussed in Section 4.

2 Multi-objective optimization algorithms

Multi-objective optimization problems arise frequently in engineering applications where several objectives need to be optimized simultaneously. Applied to power generation plant problems, Non-Dominated Genetic Algorithm II (NSGA-II), Particle Swarm Optimization (PSO) and Strength Pareto Evolutionary Algorithm II (SPEA II) have been found to be widely used in the literature. This Section presents a brief review of these algorithms for such applications. Table 1, compares briefly the main features of these algorithms.

NSGA-II

Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a powerful multi-objective optimization algorithm that is widely used in engineering and scientific applications. It is a variation of the NSGA algorithm, which is based on the concept of non-dominated sorting, where solutions in the population are classified into different "fronts" based on their dominance relationship with other solutions. NSGA-II builds on this concept by introducing several improvements that allow it to search for optimal solutions more efficiently and effectively. One of the key enhancements is the use of a crowding distance metric to maintain diversity in the population. This metric is used to encourage the selection of solutions that are spread out in the objective space, rather than focusing on a single region.

Another important improvement of NSGA-II is the use of an elitist selection mechanism. This ensures that the best solutions in the population are preserved from one generation to the next, which helps to prevent the loss of good solutions during the search process. NSGA-II also employs tournament selection, which involves selecting individuals for reproduction based on their dominance and crowding distance values. The algorithm uses binary tournament selection in the early generations to encourage diversity, and switches to crowding tournament selection in later generations to promote convergence towards the Pareto-optimal front.

Mayer et al. use NSGA-II in a multi-objective optimization problem of a household with renewable energy supply in which the net present cost and environmental footprint are the objective functions chosen to search for the Pareto-front solutions [1]. The results prove multi-objective optimization to be satisfactory to investigate trade-offs solution between two conflicting objective functions.

https://doi.org/10.52202/069564-0088

Similarly, Oyekale et al. develop a thermo-economic optimization of a solar organic Rankine cycle power plant with the NSGA-II. The Pareto-front is obtained with the objective functions of biomass mass flow rate and investment cost rate [2].

NSGA-II is also the algorithm chosen by Bolbot et al. for the optimization of a cruise ship power plant considering as objective functions the Life Cycle Cost and lifetime CO2 emissions [3]. The optimization has taken into account existing and future SOx and NOx IMO regulations, which were used as constraints in the optimization process. The algorithm has proved to succeed in finding an optimal solution that meets with these regulations.

Villalba-Herreros et al. make use of the NSGA-II in a multi-objective optimization of a power plant based on Direct Methanol Fuel Cells (DMFCs) with a CO2 capture system to power an Autonomous Underwater Vehicle (AUV) [4].

PSO

Particle Swarm Optimization (PSO) is a nature-inspired metaheuristic optimization algorithm that is widely used to solve complex optimization problems. The algorithm is based on the movement of particles in a multidimensional search space, which is designed to explore the space and find the best solution. In PSO, a population of particles represents candidate solutions, and the movement of the particles is influenced by their own best position (i.e., personal best) and the best position found by the swarm (i.e., global best). Each particle adjusts its position and velocity based on its own experience and the experience of the swarm, using a set of mathematical equations that determine the direction and speed of movement. This process is repeated over multiple iterations until a stopping criterion is met or the best solution is found.

One of the advantages of PSO is its simplicity and ease of implementation. The algorithm has a small number of parameters, which makes it easy to use and adjust for different optimization problems. PSO is also computationally efficient and can handle large and complex optimization problems, as it can quickly converge to a good solution with a small number of function evaluations. Additionally, PSO can handle both continuous and discrete optimization problems, and can be easily extended to handle multi-objective optimization problems. Despite its advantages, PSO can suffer from premature convergence and a lack of diversity in the population, which can result in suboptimal solutions. To mitigate these issues, various variants of PSO have been proposed, such as adaptive PSO, hybrid PSO, and cooperative PSO.

Vijayakumar et al. propose the use of a modified PSO algorithm in [5], in a load distribution optimization to find the lowest electric power generation cost. The results were compared with genetic algorithms and conventional PSO algorithms, offering the modified PSO the lowest electric power generation cost among them.

Azaza et al. use the PSO in a Multi-objective optimization of a hybrid micro-grid system composed of photovoltaic panels, wind turbines, diesel generators and battery storage [6]. The objective functions set were reliability, Cost of electricity (COE) and the renewable factor to minimise the use of the diesel generator.

SPEA II

Strength Pareto Evolutionary Algorithm II (SPEA II) is a multi-objective optimization genetic algorithm that uses a fitness function to evaluate the quality of solutions in the population. The fitness function considers both the solution's objective values and its distance to other solutions in the population. Solutions with high fitness are selected for the next generation, and the process is repeated to obtain a set of non-dominated solutions. SPEA II has been applied to various engineering problems, including transportation planning, manufacturing, and structural optimization. However, SPEA II can be computationally expensive for problems with a large population size.

This algorithm is used by Mehrdad et al. in [7] for the optimization of organic Rankine cycle used in a power plant. The objective functions used in the Pareto-front are the Levelized Energy Cost (LEC) and the exergy efficiency.

Dufo-López et al. make use of SPEA II in [8], where this algorithm is applied for the optimization of stand-alone photovoltaic, wind and diesel systems with battery storage. The objective functions are

https://doi.org/10.52202/069564-0088

the Levelized Cost of Energy and the equivalent CO2 life cycle emissions. The results of the optimization allowed to dimension and select the power generation devices for the plant, as well as discard others.

Table 1. Comparison features between NSGA-II, PSO and SPEA II.

Features	NSGA-II	PSO	SPEA II
Type of algorithm	Genetic	Stochastic	Genetic
Multi-objective	Yes	Not by default	Yes
Search space technique	Non-dominated sorting / crowding distance	Swarm of particles	Strength metric
Optimization criteria	Pareto dominance	Fitness function	Strength and distribution
Convergence criteria	Quality measure convergence	Fitness function convergence	Limit of space distance
Robustness	High	Lower	Higher
Computational demand	High	Light	Medium
Discontinuous functions	Yes	Struggle	Yes
Weakness	Computationally demanding	Discontinuous functions	Requires large population to maintain diversity
References	[1-4]	[5-6]	[7-8]

In summary, three different types of optimization techniques have been shown in the present Section and references of all of them related to power generation/distribution problems have been briefly explained. As can be observed, regardless of the method used, in all cases the economics are one of the objective functions of the Pareto-front. The second objective function is related either to the efficiency of the system or the emissions produced.

3 Methodology

The main focus of the investigation outlined in this work is shown in Figure 1. The figure shows the main overview of the algorithm methodology. In the following Sections 3.1 to 3.5 the steps of this workflow are explained.

3.1 Input data - Operational profile and fuels

The initial conditions that are the basis of the optimization process are given by the operational profile of the vessel and the fuels used.

The operational profile is broken down into endurance of the vessel, electrical demand and heat demand.

The electrical demand considered is defined as the sum of the propulsion power in a vessel with electric propulsion, and the auxiliary power demand of the vessel. This auxiliary power initially does not consider the electrical demand needed to make the power plant operational, that is, the power of the balance of the plant (BoP) as it depends on the size of the power plant itself. The BoP is sized in an iterative process further explained in Section 3.2.

The selection of one, two, three, four or all the fuels to be considered during the optimization process will depend on the specific case to which the methodology presented in this work is applied.

Regarding the fuels used onboard, five alternative fuels are considered: liquid hydrogen (LH2), methanol (MeOH), ammonia (NH3), liquid natural gas (LNG) and biofuels.

The different power plant components will be dimensioned according to the required demands as explained in Section 3.2.

Lastly, the endurance input is fed directly to the mathematical modelling of the algorithm as explained in Section 3.2.

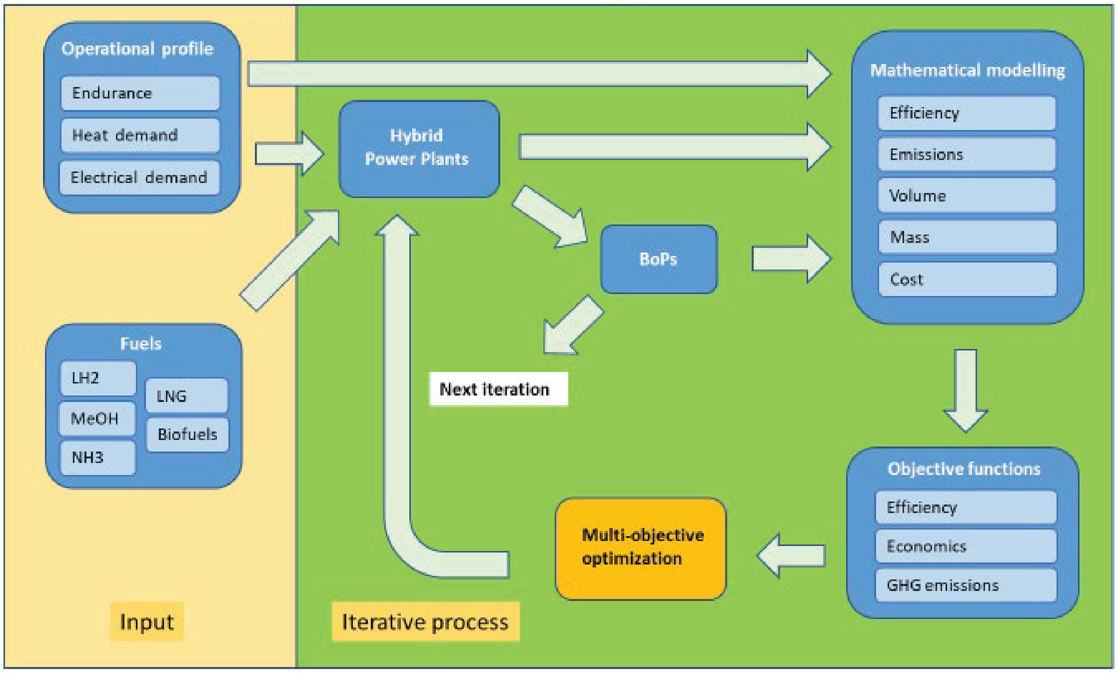

Figure 1. Methodology diagram of the multi-objective algorithm.

3.2 Hybrid Power Plants

The input parameters defined in Section 3.1 are introduced into the iterative process shown in Figure 2.

Electrical and heat demands of the operational profile as well as the fuels selected are used to establish an initial dimensioning of the power generation devices of the hybrid power plants.

During the first iteration, the population of hybrid power plants is created randomly, varying the power capacity of the different power generation devices.

The power plant components of the marine hybrid power plants are:

- PEM Fuel Cells (electricity generation)
- Generator sets (electricity generation)
- Battery energy storage (electricity storage/generation)
- Boiler (heat generation)
- Heat recovery systems (heat generation)

The set of hybrid power plants obtained in this step form the population that is subjected to the optimization process in the algorithm. In this respect it will be assumed that each individual of the population will make use of only one of the fuels. This is an extended practice in the maritime industry (although the use of two different fuels onboard a ship is also common) in order to minimize the amount of equipment needed to make the power plant functional.

 https://doi.org/10.52202/069564-0088

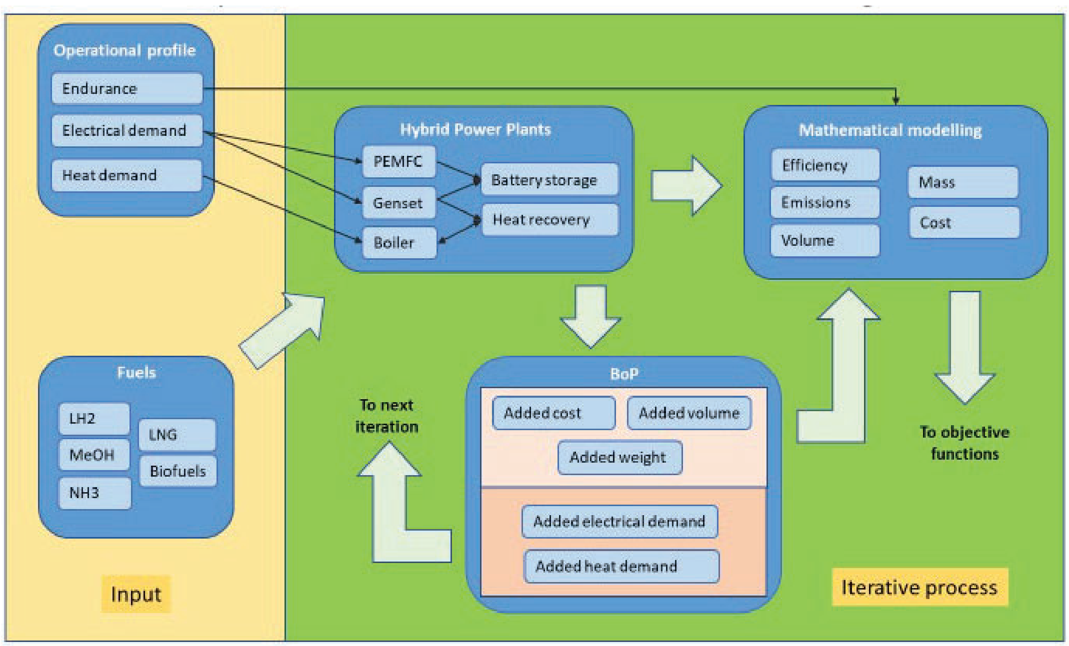

Figure 2. Workflow diagram of the mathematical modelling.

3.3 Mathematical modelling of hybrid power plants

Each individual of the hybrid power plants will have its own configuration of fuel, PEM Fuel Cells, generator sets, battery storage, boiler and heat recovery systems. For each individual, the mathematical model is the step in which the performance of the plant is assessed. Efficiency, emissions, volume required on board, mass and cost of the plant are calculated in this step.

The endurance of the vessel is also introduced at this step. Once the efficiency of the hybrid power plant is known, it will be possible to assess the volume of the fuel storage as well as its mass contributions.

3.3.1 Mathematical modelling of the balance of plants (BoPs)

Simultaneously to the mathematical modelling of the hybrid power plant individuals, the balance of plant (BoP) is also assessed. BoP is an important component of a marine power plant that refers to all of the auxiliary systems and equipment required to support the power generation process. It involves a wide range of systems and equipment, such as the electrical grid connection, transformers, control systems, fuel supply systems, reformers, exhaust systems, lube oil systems, compressed air or refrigeration systems.

Combining different power generation and power storage devices in a hybrid power plant needs to take into account that there will be interfaces and share of equipment between them, thus affecting the BoP. Such combination is taken into account in the BoP in order to create a model that considers the integration of different power plant devices.

The calculation of the BoP for each individual will allow to estimate the additional contributions of electrical demand, heat demand, cost, volume required onboard the vessel and mass.

As mentioned in Section 3.1, added electrical demand and heat demand will be used in the next iteration process to dimension the next generation of hybrid power plants. This will allow to estimate future individuals of hybrid power plants taking into account these contributions, so that after a few generations the additional electrical and heat demands will tend to zero.

Added cost, volume and mass parameters are combined with the contributions of these parameters calculated for the hybrid power plants in the mathematical model.

3.4 Objective functions

In Section 2, works found in the literature regarding multi-objective optimization cases applied to the dimensioning of hybrid power plants have been analysed. The analysis has shown that the objective functions selected to carry out the multi-objective optimizations are in most cases focused on costs combined with efficiency or greenhouse gas emissions. These objective functions entail the search of trade-off solutions in which a Pareto-Front is obtained in the multi-objective optimization process. This is one of the key elements that is seek in the present work, as the aim of the methodology proposed is to help during the decision-making of the optimum hybrid power plant. A range of hybrid power plants forming a Pareto-Front will give the end-user the possibility to take a decision based on a set of criteria that have opposite impacts.

In Figure 3 it is shown the workflow of how the parameters calculated in the mathematical model are distributed into the objective functions.

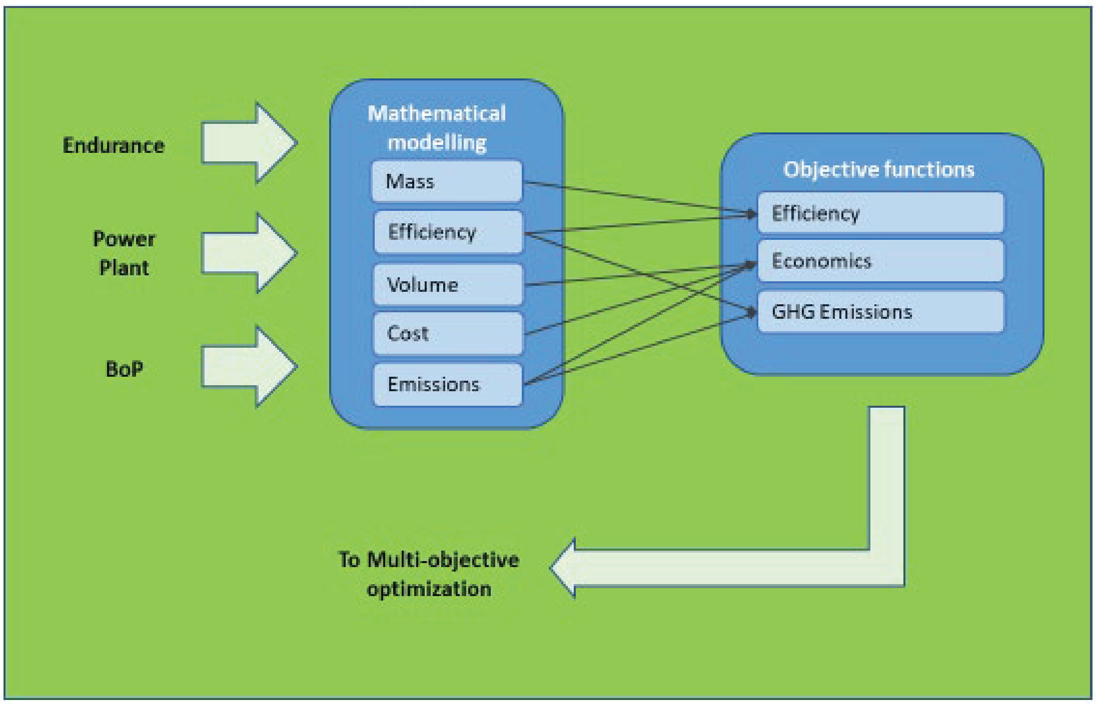

Figure 3. Workflow from mathematical modelling to objective functions.

3.4.1 Efficiency

The objective function of efficiency allows to give information of the performance of the hybrid power plant. Besides, it is a parameter that will not be subject to considerable changes in mid or long-term perspectives. Even though devices like the PEM Fuel Cells are emerging technologies in the maritime, efforts on their development are being focused on reducing their investment cost through the use of new materials. Therefore, this objective function will have the quality of a stability with high reliability.

3.4.2 Economics

The objective function of the economics has contributions from three different parameters of the mathematical model: costs, volume and emissions.

As it is reasonable, the costs of the hybrid power plant obtained in the mathematical model, which are calculated in capital expenses (CAPEX) and operational expenses (OPEX) of the plant, contribute greatly to this objective function.

https://doi.org/10.52202/069564-0088

The volume of the hybrid power plant, and the volume on the vessel required to store the fuel, can affect, depending on the type of vessel, to other spaces such as cargo, that would report a benefit otherwise. Therefore, the volume parameter calculated in the mathematical model can also influence the objective function of economics.

The emissions, which depending on the power generation device, can be composed of greenhouse gases and others such as NOx, SOx or PM, can be subject to penalties from the international regulatory organizations. Therefore, this is also taken into account in this objective function.

3.4.3 GHG Emissions

The purpose of objective function of greenhouse gas emissions is to be evaluate and compare the environmental impact of the hybrid power plants. Taking the operational profile of the vessel allows to calculate the mass of CO2 emitted to the atmosphere during in a specific amount of time. For each hybrid power plant analysed, this mass will be calculated and serve as basis of this objective function.

3.5 Multi-objective optimization and iteration

The multi-objective optimization is performed with the three objective functions defined in Section 3.4, economics, efficiency and GHG emissions. As a result of the optimization, a set of new hybrid power plants are obtained and introduced into the next iteration. The added electrical demand and added heat demand are introduced also in the next iteration, as explained in Section3.2, and their values will tend to stabilize as the number of iterations increase. The workflow of this step is shown in Figure 4.

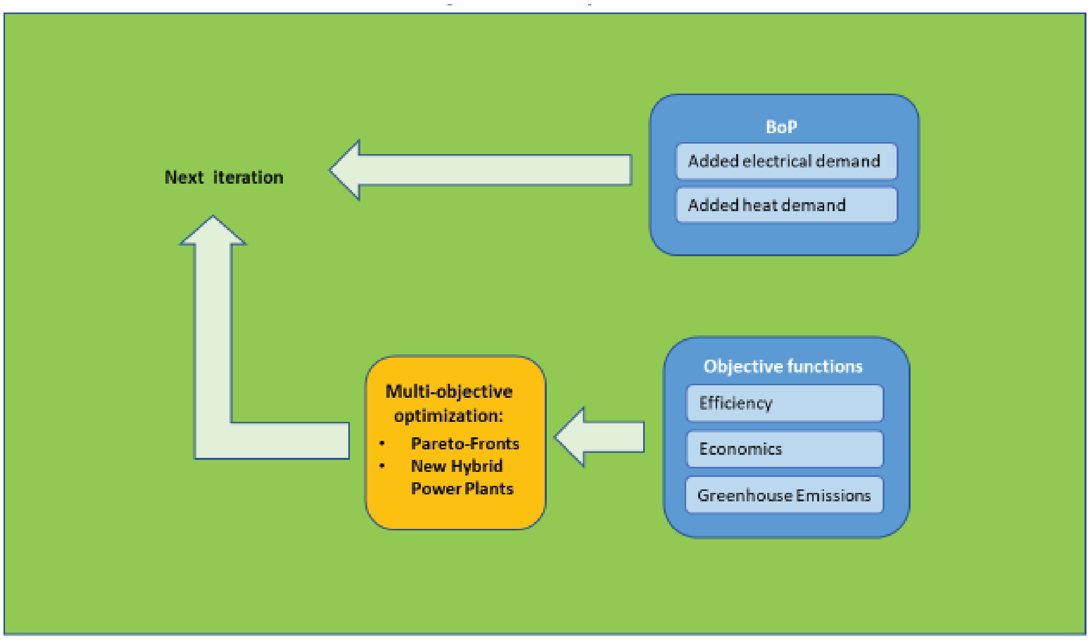

Figure 4. Workflow of multi-objective optimization.

The Pareto-Front generated in the optimization process will be based on the three objective functions defined. To take into account the three objective functions simultaneously, the Pareto-Front is represented in a 3-dimensional graph.

4 Discussion

In the present work a methodology to optimize maritime hybrid power plants fuelled with alternative fuels has been presented. In Section 2, the results of a search of optimization algorithms used in the literature applied to cases of dimensioning hybrid power plants are presented. Three optimization algorithms (NSGA-II, PSO and SPEA-II) have been found with positive results throughout the cases applied. Among the cases found in the literature, two objective functions are normally used in the optimization process, from a group of three, efficiency, economics and GHG emissions. Pareto-Fronts of two objective functions are therefore the outcome of these works. The authors find that the three objective functions mentioned are of high relevance in the decision-making process of dimensioning a maritime hybrid power plant. For this reason, it has been decided that the methodology proposed in Section 3 makes use of the three objective functions simultaneously. Pareto-fronts are therefore represented in 3-dimensional graphs, with each x-y-z axis associated to each of the objective functions.

Hybrid power plants require to integrate different power generation devices working together in harmony. In order to achieve this integration, the auxiliary systems to make the hybrid power plant operational, known as the balance of plant (BoP), have a higher level of complexity compared to power plants with single power generation devices. For this reason, in the methodology proposed in Section 3, the BoP has been given significant relevance and importance within the algorithm. For each hybrid power plant, its BoP will have its specific needs, which results in specific mass of the equipment, volume required on board, costs, but also electrical power demand and heat demand. The workflow of the BoP is shown in Figure 2. As the BoP is based on the information of the hybrid power plant, the added electrical demand and heat demand are no longer considered in the current iteration step, otherwise this would affect the dimensioning of the hybrid power plant that has been already stablished. Therefore, added electrical demand and heat demand are introduced in the next iteration of the algorithm. As the number of iterations increase, the hybrid power plants tend to be dimensioned matching the needs of the BoP. Therefore, the added electrical demand and heat demand of the BoP will tend to zero as the iterations grow.

As explained in Section 3.1, one part of input data to be applied to the algorithm comes from the operational profile of a vessel with electric propulsion. Electrical power demand and heat demand are used to dimension initially the hybrid power plants. To do so, the reference points from which these demands are considered have to be common for all types of hybrid plants., e.g., the ship propeller, that has a mechanical demand to be moved, has a prime mover that is an electric motor, this electric motor has an electrical demand to move the propeller that can be common for any given hybrid power plant considered in this work. Future works that could include mechanical propulsion of the vessel would need to take this into account.

5 Conclusions

The emerging technologies that are being implemented in the maritime field regarding the use of alternative fuel devices such as PEM Fuel Cells have a direct impact on the power plants of vessels. The combination of different power generation devices entails a level of hybridization of power plants that requires a higher complexity to make the hybridized power plant to function in harmony. To solve this problem, a methodology for a multi-objective optimization process that will help during the decision-making process of the power plant has been proposed. The main conclusions obtained from are summarized below:

- The methodology proposed is able to integrate the different power generation devices through specific balance of plant oriented to each hybrid power plant considered.
- Three objective functions (efficiency, economics and GHG emissions) have been defined. The objective functions will allow to create a 3-dimensional Pareto-Front to assist the user on the decision-making process of the optimum hybrid power plant.
- The point of reference from the electrical demand and heat demand given by the operational profile of the vessel needs to be common for all hybrid power plants.

Acknowledgements

This work has been carried out thanks to the Project GreenH2CM funded by MCIN/AEI/10.13039/501100011033, by “NextGenerationEU/PRTR” and the Regional Government of Madrid and to the Grant PID2021-124263OB-I00 funded by MCIN/AEI/10.13039/501100011033 and by “ERDF a way of making Europe”.

https://doi.org/10.52202/069564-0088

References

[1] M. J. Mayer, A. Szilágyi, and G. Gróf, “Environmental and economic multi-objective optimization of a household level hybrid renewable energy system by genetic algorithm,” Appl Energy, vol. 269, p. 115058, 2020, doi: https://doi.org/10.1016/j.apenergy.2020.115058.

[2] J. Oyekale, M. Petrollese, and G. Cau, “Multi-objective thermo-economic optimization of biomass retrofit for an existing solar organic Rankine cycle power plant based on NSGA-II,” Energy Reports, vol. 6, pp. 136–145, 2020, doi: https://doi.org/10.1016/j.egyr.2019.10.032.

[3] V. Bolbot, N. L. Trivyza, G. Theotokatos, E. Boulougouris, A. Rentizelas, and D. Vassalos, “Cruise ships power plant optimisation and comparative analysis,” Energy, vol. 196, p. 117061, 2020, doi: https://doi.org/10.1016/j.energy.2020.117061.

[4] A. Villalba-Herreros, Ó. Santiago, L. Magistri, and T. J. Leo, “Autonomous Underwater Vehicle Powered by Direct Methanol Fuel Cell-Based Power Plants: A Quick Preliminary Design Model,” Applied Sciences, vol. 10, no. 21. 2020. doi: 10.3390/app10217687.

[5] T. Vijayakumar and V. R, “Efficient Energy Load Distribution Model using Modified Particle Swarm Optimization Algorithm,” Journal of Artificial Intelligence and Capsule Networks, vol. 2, pp. 226–231, Feb. 2021, doi: 10.36548/jaicn.2020.4.005.

[6] M. Azaza and F. Wallin, “Multi objective particle swarm optimization of hybrid micro-grid system: A case study in Sweden,” Energy, vol. 123, pp. 108–118, 2017, doi: https://doi.org/10.1016/j.energy.2017.01.149.

[7] S. Mehrdad, R. Dadsetani, A. Amiriyoon, A. S. Leon, M. Reza Safaei, and M. Goodarzi, “Exergo-Economic Optimization of Organic Rankine Cycle for Saving of Thermal Energy in a Sample Power Plant by Using of Strength Pareto Evolutionary Algorithm II,” Processes, vol. 8, no. 3. 2020. doi: 10.3390/pr8030264.

[8] R. Dufo-López et al., “Multi-objective optimization minimizing cost and life cycle emissions of stand-alone PV–wind–diesel systems with batteries storage,” Appl Energy, vol. 88, no. 11, pp. 4033–4041, 2011, doi: https://doi.org/10.1016/j.apenergy.2011.04.019.