From Theory to Practice: Bridging Multi-Objective Optimization with Renewable Energy Systems

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Abstract

This report investigates the application of Multi-Objective Optimization (MOO) to problems with conflicting objectives, emphasizing the complexity and nuances of decision-making in diverse systems. As a case study, we model energy systems in two operational modes: Island Mode, which requires self-sufficiency in energy production, and Grid Mode, which permits trading with an external grid. These scenarios serve as test beds for our MOO algorithms, demonstrating how such approaches can effectively resolve the inherent conflicts between environmental impact, economic viability, and system reliability. The findings contribute to the broader understanding of MOO's potential in achieving balanced solutions in multi-criteria environments.

1 Introduction

In the evolving landscape of technological advancement and environmental consciousness, Multi-Objective Optimization (MOO) emerges as a pivotal tool, especially in scenarios where multiple conflicting objectives need to be reconciled. This report delves into the realm of MOO, utilizing the pymoo Python library, which integrates advanced evolutionary algorithms such as NSGA-II[1] and NSGA-III[2]. These algorithms are pivotal in demonstrating the efficacy of MOO across various complex scenarios, including benchmark problems like Dent and more intricate models like DTLZ7[3].

A significant focus of this study is the application of MOO to energy systems, particularly in two operational modes: Island and Grid. Island Mode requires the energy system to be self-sufficient, focusing on optimizing CO2 emissions, cost, and power balance. Grid Mode, conversely, allows interaction with the power grid, optimizing for cost, CO2 emissions, and grid power ratio. This exploration offers a comprehensive analysis of MOO's potential in orchestrating a symphony of objectives, leading to sustainable and economically viable solutions. Through this study, we aim to bridge the gap between theoretical MOO concepts and practical implementation, contributing significantly to the advancement of optimization techniques in energy systems and beyond.

The report's structure includes: Section 2, which introduces MOO and the pymoo library, focusing on NSGA-II and NSGA-III algorithms; Section 3, evaluating these algorithms against benchmarks like Dent and DTLZ7; Section 4, detailing the formulation and application of MOO in energy systems for Island and Grid Modes; Section 5, discussing the findings and their implications for cost, CO2 emissions, and power stability; and Section 6, summarizing the study and outlining future research directions.

This study draws significant inspiration from the work of Ming et al. [4], which elucidates an enhanced multi-objective evolutionary algorithm's role in optimizing hybrid renewable energy systems. Their methodological advancements and findings provide a foundational pillar for our exploration of MOO within energy systems in both Island and Grid modes.

2 Foundations of Multi-Objective Optimization

Multi-Objective Optimization (MOO) represents a crucial branch of optimization theory, primarily concerned with solving problems that have multiple, often conflicting objectives. Traditionally, optimization problems focus on finding the best solution concerning a single criterion. However, in real-world scenarios, decisions are rarely based on a singular objective. MOO provides a framework for these complex situations, accommodating multiple objectives and finding a set of optimal solutions, often referred to as Pareto-optimal solutions.

The concept of Pareto optimality is central to MOO. A solution is considered Pareto-optimal if no objective can be improved without worsening at least one other objective. The set of all Pareto-optimal solutions forms what is known as the Pareto front. This front represents the trade-off surface where decision-makers can understand how one objective affects the others and thus make informed choices based on their preferences or priorities. As illustrated in Figure 1, the Pareto front demonstrates the spectrum of optimal solutions achievable in a two-objective optimization scenario, representing the trade-off between structural integrity and design efficiency in the Truss2D problem.

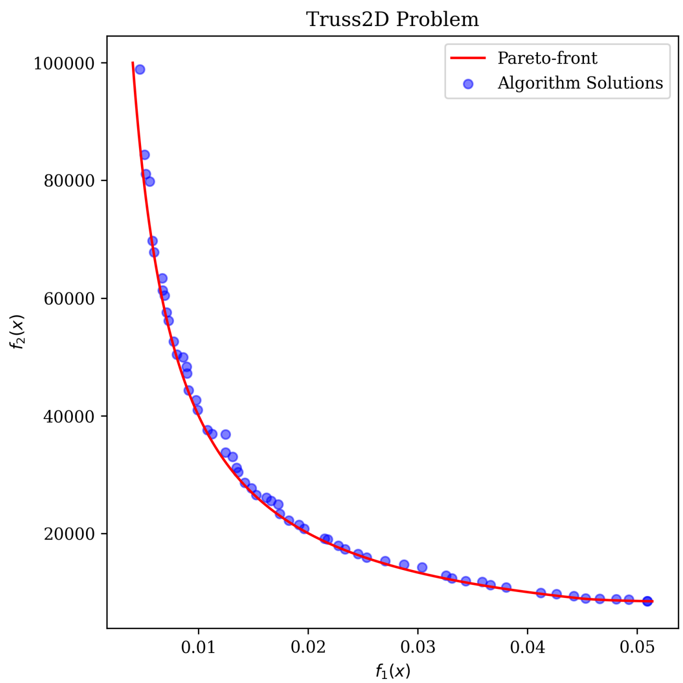

Figure 1: Pareto front of the Truss2D[5] problem obtained using an MOO algorithm. The blue dots represent algorithm solutions that approximate the true Pareto front, shown in red.

In the realm of MOO, the pymoo[6] library emerges as a powerful and versatile tool. pymoo is an open-source Python library that provides algorithms and functionalities for multi-objective optimization. It includes a range of evolutionary algorithms, which are particularly well-suited for MOO due to their ability to handle complex optimization landscapes and find diverse sets of solutions.

Among the evolutionary algorithms implemented in pymoo, NSGA-II (Non-dominated Sorting Genetic Algorithm II) and NSGA-III are prominent. NSGA-II[1] is renowned for its efficiency and effectiveness in finding a well-distributed set of Pareto-optimal solutions. It operates on the principles of non-dominated sorting and uses a crowding distance mechanism to maintain diversity in the solution set. NSGA-III[2], an extension of NSGA-II, is designed for problems with many objectives. It introduces a reference point-based approach to maintain diversity, making it effective for handling higher-dimensional objective spaces.

The pymoo library's modular structure and comprehensive API make it an ideal choice for researchers and practitioners in MOO. Its ability to integrate custom problem definitions, alongside standard benchmark problems, facilitates extensive experimentation and analysis in diverse MOO scenarios

3 Benchmark Problems in Multi-Objective Optimization

Benchmarking plays an indispensable role in the evaluation of Multi-Objective Optimization (MOO) algorithms. It involves the use of standardized problems that are designed to rigorously test the algorithms' capabilities. These benchmarks expose the strengths and limitations of MOO algorithms, providing insights into their performance across different optimization landscapes. In this study, we consider two well-known benchmark problems: the Dent problem and the DTLZ7 problem, which help us assess the algorithms' efficiency, robustness, and ability to maintain solution diversity.

3.1 Analysis of the Dent Problem

The Dent problem stands as a fundamental benchmark in Multi-Objective Optimization (MOO) due to its clarity in showcasing the trade-offs between two conflicting objectives. It is designed to test an algorithm's ability to find diverse Pareto-optimal solutions.

The unconstrained version of the Dent problem is expressed as:

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f_1(x) = 0.5\left(\sqrt{1+(x_0+x_1)^2}\sqrt{1+(x_0-x_1)^2}+(x_0-x_1)\right)+0.85e^{-(x_0-x_1)^2}, \\ & f_2(x) = 0.5\left(\sqrt{1+(x_0+x_1)^2}\sqrt{1+(x_0-x_1)^2}-(x_0-x_1)\right)+0.85e^{-(x_0-x_1)^2}, \\ \text{subject to} \quad & -1.5 \leq x_0, x_1 \leq 1.5. \end{aligned} \tag{1}$$

The constrained variant introduces boundary conditions to the objectives, narrowing the focus to the most significant region of trade-off without substantially increasing the problem's complexity.

The constrained Dent problem is expressed as:

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f_1(x) = 0.5\left(\sqrt{1+(x_0+x_1)^2}\sqrt{1+(x_0-x_1)^2}+(x_0-x_1)\right)+0.85e^{-(x_0-x_1)^2}, \\ & f_2(x) = 0.5\left(\sqrt{1+(x_0+x_1)^2}\sqrt{1+(x_0-x_1)^2}-(x_0-x_1)\right)+0.85e^{-(x_0-x_1)^2}, \\ \text{subject to} \quad & -1.75 \leq f_1(x) \leq 1.75, \\ & -1.75 \leq f_2(x) \leq 1.75, \\ & -1.5 \leq x_0, x_1 \leq 1.5. \end{aligned} \tag{2}$$

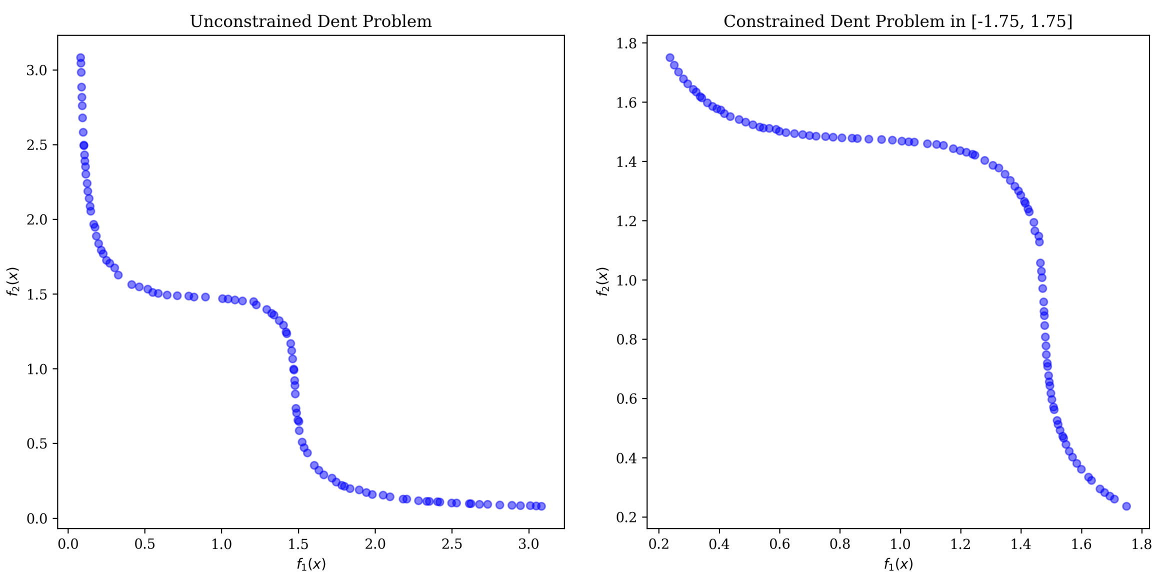

Figure 2: Pareto fronts for the Dent problem: Unconstrained (left) and Constrained (right).

Figure 2 displays the Pareto fronts for both the unconstrained and constrained Dent problems. The constraints effectively zoom in on the critical trade-off area, as seen in the shift of the Pareto front, without introducing significant complexity to the problem. This characteristic underscores the utility of the pymoo library, which simplifies the integration of constraints and demonstrates the robustness of the algorithms in efficiently approximating the true Pareto front.

3.2 Analysis of the DTLZ7 Problem

The DTLZ7 benchmark is part of the DTLZ test suite, a collection of problems designed to assess and benchmark the performance of Multi-Objective Optimization (MOO) algorithms. This particular problem is structured to challenge optimization techniques on several fronts: it features a highly disconnected Pareto front and is scalable, meaning that the number of objectives can be expanded, increasing the complexity of the problem.

In this analysis, we applied both NSGA-II and NSGA-III algorithms to solve the DTLZ7 problem. The results revealed interesting contrasts between the two algorithms. NSGA-II managed to identify the Pareto fronts; however, it displayed an uneven distribution of solutions—certain areas were overpopulated while others were sparse. On the other hand, NSGA-III, with its reference direction strategy, successfully achieved a uniform coverage of the entire Pareto front. The ability of NSGA-III to uniformly capture each disconnected Pareto front emphasizes its robustness in handling problems with multiple objectives, particularly when it comes to maintaining solution diversity across the entire front. This uniformity is crucial in real-world applications where a fair representation of all trade-offs is required for effective decision-making.

As shown in Figure 3, the DTLZ7 problem solved by NSGA-II and NSGA-III illustrates the different capabilities of these algorithms. NSGA-II results in an uneven distribution across Pareto fronts, whereas NSGA-III achieves a more uniform and complete coverage

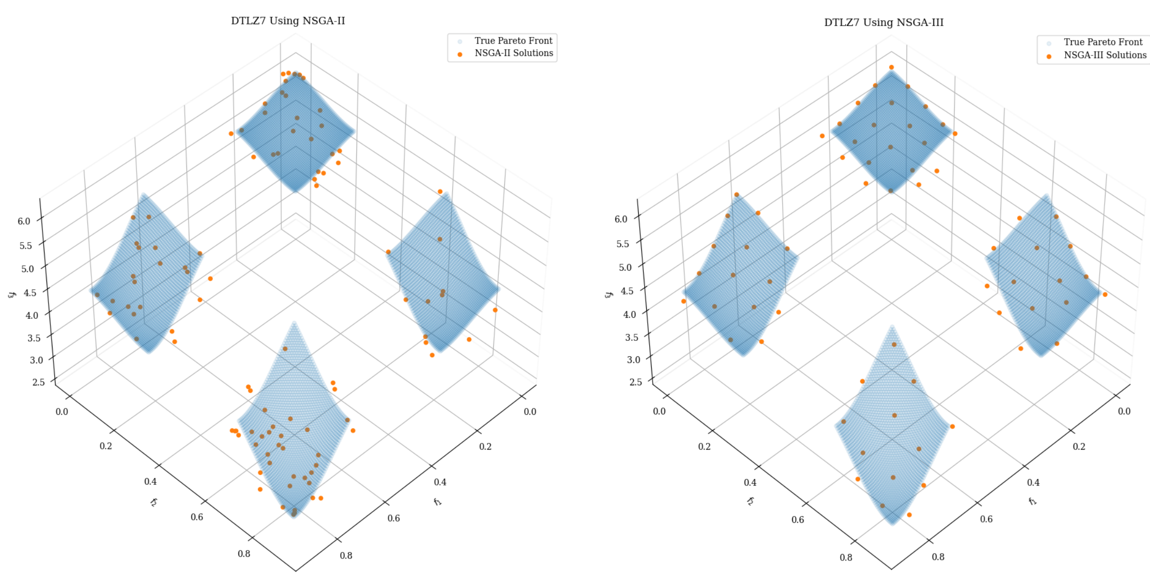

Figure 3: Comparison of DTLZ7 optimization results: NSGA-II (left) shows uneven distribution across Pareto fronts, whereas NSGA-III (right) demonstrates uniform coverage.

4 Modeling the Energy System

This section presents a comprehensive mathematical model of an energy system that integrates renewable sources like solar panels and wind turbines, supplemented with energy storage in batteries. The system's design caters to sustainable and cost-effective energy demand fulfillment, adapting to variable environmental conditions. Depending on its operational mode, it may also incorporate generators.

The model operates in two distinct modes: Island and Grid. In Island Mode, the system functions autonomously, managing energy production and consumption independently, without external support. This mode emphasizes self-sufficiency and sustainable management of resources. Conversely, Grid Mode extends the system's capabilities, enabling economic interactions with the power grid. In this mode, the system can sell excess energy or purchase additional power to meet its demands, reflecting a balance between economic viability and energy sustainability.

The mathematical formulation of this energy system assesses its performance across multiple dimensions: sustainability, economic feasibility, and reliability. It quantifies the output of renewable energy sources, the dynamics of energy storage, and the implications of grid interactions. This model forms the foundation for optimizing the energy system's operation, ensuring it meets its objectives effectively in both Island and Grid modes.

4.1 Mathematical Model of the HRES

The mathematical model includes the following functions to simulate the energy system's performance:

Power Output Function

The hourly energy production $P_{\text{total}}(t)$ is determined by the collective output of solar panels and wind turbines, considering the hourly variability of environmental factors:

$$P_{\text{total}}(t) = N_{\text{solar}} \cdot P_{\text{solar}} \cdot W_{\text{solar}}(t) + N_{\text{wind}} \cdot P_{\text{wind}} \cdot W_{\text{wind}}(t) \tag{3}$$

Energy Demand Function

The energy demand at any given time t is a function of the total daily demand D_{total}, distributed over the day according to a weighting factor $W_{\text{demand}}(t)$ that accounts for hourly fluctuations:

$$D(t) = \left(\frac{D_{\text{total}}}{T}\right) \times W_{\text{demand}}(t) \tag{4}$$

where T is the total number of time intervals in the day.

State of Charge, Energy Deficit, and Energy Excess Calculations

The State of Charge (SOC) of the batteries, along with the energy deficit and energy excess, are updated at each time step as follows:

$$SOC(t) = SOC(t-1) + P_{\text{total}}(t) - D(t) \tag{5}$$

$$E_{\text{deficit}}(t) = |\min\{SOC(t), 0\}|, \quad SOC(t) = \begin{cases} 0, & \text{if } E_{\text{deficit}}(t) > 0 \\ SOC(t), & \text{otherwise} \end{cases} \tag{6}$$

$$E_{\text{excess}}(t) = \max\{SOC(t) - (N_{\text{batt}} \times B_{\text{cap}}), 0\}, \quad SOC(t) = \begin{cases} N_{\text{batt}} \times B_{\text{cap}}, & \text{if } E_{\text{excess}}(t) > 0 \\ SOC(t), & \text{otherwise} \end{cases} \tag{7}$$

These equations dynamically update the SOC based on the balance between power production, demand, and the storage capacity of the batteries. Energy deficits and excesses are calculated to reflect the system's performance in real-time, impacting the SOC accordingly.

Handling Energy Deficit and CO2 Emission Calculation

The approach to managing energy deficit and calculating CO2 emissions varies between Island and Grid modes, primarily due to the involvement of diesel generators and the grid.

In Island Mode, diesel generators cover the entire energy deficit, and CO2 emissions are directly proportional to the deficit.

$$E_{\text{CO2}}^{\text{island}}(t) = E_{\text{CO2 rate}} \cdot \frac{E_{\text{deficit}}(t)}{P_{\text{diesel}}} \tag{8}$$

In Grid Mode, diesel generators are used up to their capacity, and any remaining deficit is compensated by purchasing power from the grid.

$$E_{\text{CO2}}^{\text{grid}}(t) = E_{\text{CO2 rate}} \times \min \left\{ \frac{E_{\text{deficit}}(t)}{P_{\text{diesel}}}, N_{\text{gen}} \right\}, \tag{9}$$

$$\begin{aligned} P_{\text{gen}}(t) &= N_{\text{gen}} \times P_{\text{diesel}}, \\ E_{\text{grid}}(t) &= \max \left\{ E_{\text{deficit}}(t) - P_{\text{gen}}(t), 0 \right\} \end{aligned} \tag{10}$$

Cost Function Formulation

The cost functions for both Island and Grid modes are formulated to account for the operational expenses of the energy system, including the costs of renewable energy sources, diesel fuel, and, in the case of Grid Mode, generators and grid transactions.

This function in Island Mode includes costs associated with solar panels, wind turbines, and diesel fuel.

$$C_{\text{island}} = (N_{\text{solar}} \cdot C_{\text{solar}}) + (N_{\text{wind}} \cdot C_{\text{wind}}) + (N_{\text{liters}} \cdot C_{\text{diesel}}) \tag{11}$$

In Grid Mode, additional costs for generators and net expenses or revenues from grid interactions are considered. This is calculated as the sum of costs for each component, factoring in the energy purchased from and sold to the grid.

$$\begin{aligned} C_{\text{grid}} =& (N_{\text{solar}} \cdot C_{\text{solar}}) + (N_{\text{wind}} \cdot C_{\text{wind}}) + (N_{\text{liters}} \cdot C_{\text{diesel}}) \\ &+ (N_{\text{gen}} \cdot C_{\text{gen}}) + (E_{\text{grid}} \cdot W_{\text{grid}}) - (E_{\text{excess}} \cdot W_{\text{grid}}) \end{aligned} \tag{12}$$

Power Balance Penalty

The power balance penalty function in Island Mode penalizes deviations from optimal energy production and consumption. It assigns a higher penalty for excess energy, reflecting the importance of avoiding energy wastage:

$$P_{\text{balance}} = \|E_{excess}\|_2 + 0.5 \times \|E_{deficit}\|_2 \tag{13}$$

4.2 Objective Function Formulation

In the HRES model, the optimization goals differ by mode. In isolated-island mode, the focus is on minimizing cost, CO2 emissions, and a power balance penalty, ensuring energy system stability. In grid-connected mode, the objectives are minimizing cost, CO2 emissions, and grid energy dependency.

$$\min F = \begin{cases} \min(C_{\text{total}}, E_{\text{CO2}}^{\text{island}}, P_{\text{balance}}), & \text{for the isolated-island mode,} \\ \min(C_{\text{total}}, E_{\text{CO2}}^{\text{grid}}, E_{\text{grid}}), & \text{for the grid-connected mode.} \end{cases} \tag{14}$$

This formulation seeks to find the optimal balance between cost efficiency, environmental sustainability, and system reliability, which are the cornerstones of the HRES operation.

The operational workflows of both Island and Grid modes are systematically illustrated in Figures 5 and 6, outlining the sequence of actions for energy management and decision-making in the respective systems.

4.3 Constants and Simulation Parameters

In the simulation of the energy system, a set of constants and parameters are utilized to model the dynamics accurately. These constants reflect the production capabilities of the solar panels and wind turbines, the costs associated with each component, and the overall energy demand the system aims to satisfy. The environmental impact is quantified in terms of CO2 emissions. Table 1 and Figure 4 provide an overview of these constants.

The constants used in the simulations are based on real-world data and estimations. The total daily demand, D_{total}, is based on the annual energy consumption of the Technical University of Crete campus, amounting to 1,569,597 kWh. Divided by 365, this figure represents the daily demand without renewable energy sources [7].

Solar weights are derived from irradiance data for the location of the University of Crete in Heraklion for the month of June, provided by the Photovoltaic Geographical Information System (PVGIS) of the European Union [8]. The remaining constants are obtained through online research and are not as extensively derived as the demand and solar weights but are based on industry standards and best practices.

Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
P_{solar}	0.35 kW	C_{solar}	€250	D_{total}	4300 kWh
P_{wind}	5 kW	C_{wind}	€5000	C_{diesel}	€1.6/kWh
P_{gen}	4 kW	C_{gen}	€1400	E_{CO2}	2.7 kg/kWh
B_{cap}	1 kWh	C_{batt}	€140		

Table 1: Constants for Energy System Model

The figure below illustrates the hourly weights for solar and wind energy production along with the energy demand pattern, which are pivotal in determining the performance of the energy system throughout the day.

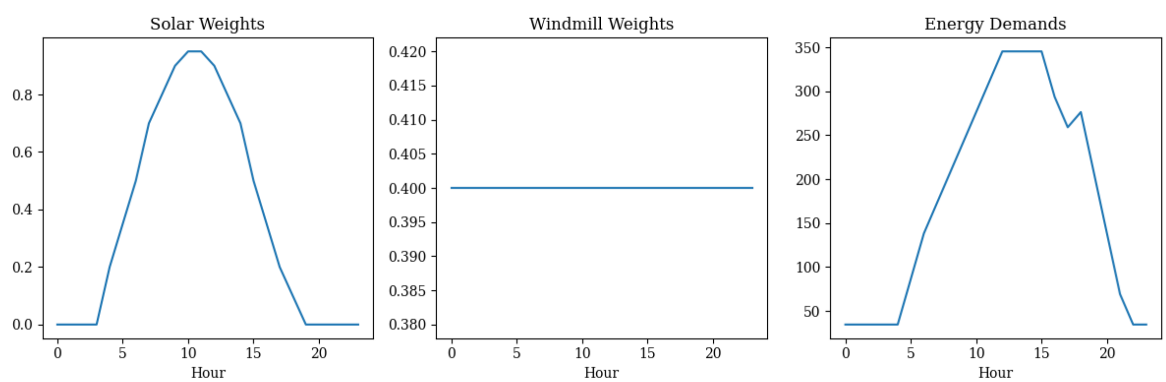

Figure 4: Hourly weights for solar and wind energy production along with energy demand.

These values are essential in formulating the operational strategy for the energy system, guiding the optimization process to balance cost, efficiency, and environmental impact.

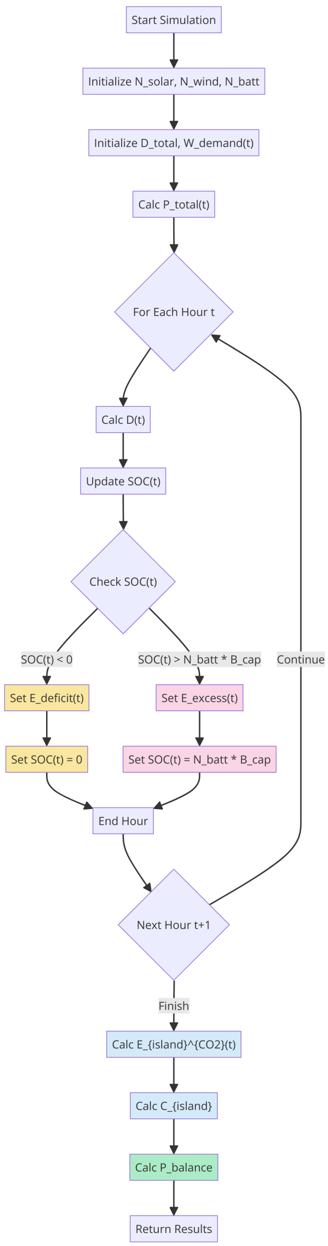

Figure 5: Island Mode Flowchart

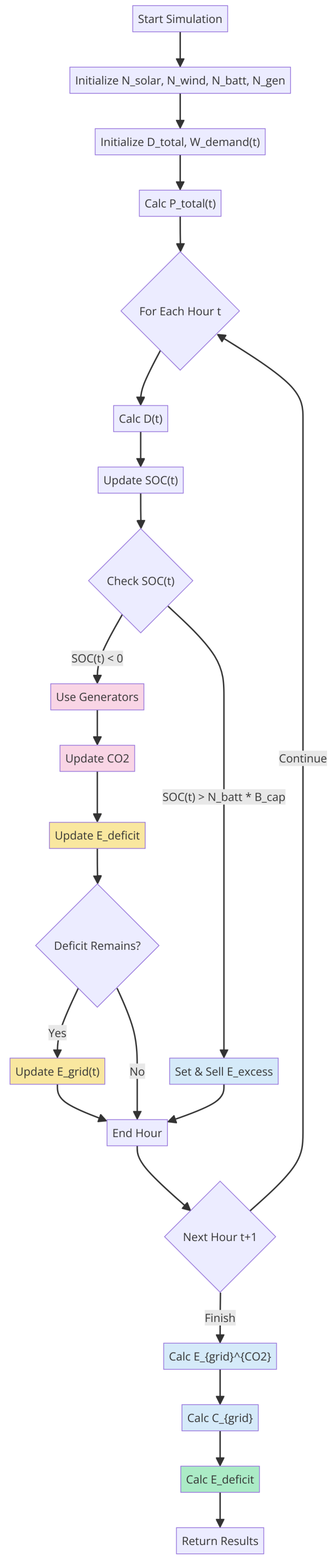

Figure 6: Grid Mode Flowchart

5 Results

This section delves into the detailed analysis of the results obtained from the application of Evolutionary Multi-Objective Optimization (MOO) algorithms to our energy system in both Grid and Island Modes. The analysis is centered around the Pareto fronts generated by the NSGA-II and NSGA-III algorithms, which reveal the trade-offs between the system's CO2 emissions, economic costs, and operational metrics such as grid-supplied power. Tables presenting specific optimization points are examined to understand the implications of these trade-offs in practical scenarios.

5.1 Analysis of Island Mode Results

The Pareto front for the Island Mode provides insight into the multi-objective optimization of CO2 emissions and system cost, with the penalty as a measure of balance efficiency. In the visualization, the front descends steeply from the right, representing a regime where reducing CO2 emissions significantly increases the cost. Progressing towards the U-shaped bend, the plot indicates an area where CO2 reduction can be achieved with a comparatively smaller increase in cost, representing an economically feasible trade-off.

The optimization points for Island Mode reflect two scenarios of interest. At the far right of the Pareto front, the scenario with zero CO2 emissions is depicted. This environmentally ideal situation is achieved using an extensive array of solar panels and wind turbines, supported by ample battery storage, corresponding to the first optimization point with a higher cost, as shown in the table.

Conversely, the point at the bottom of the U-shape on the Pareto front identifies the configuration with the lowest penalty cost. This setup involves a slightly reduced solar and wind capacity, maintaining the same battery storage, leading to non-zero CO2 emissions (600.405 kg) but achieving a substantial cost reduction. This second optimization point represents a pragmatic balance between environmental and economic considerations.

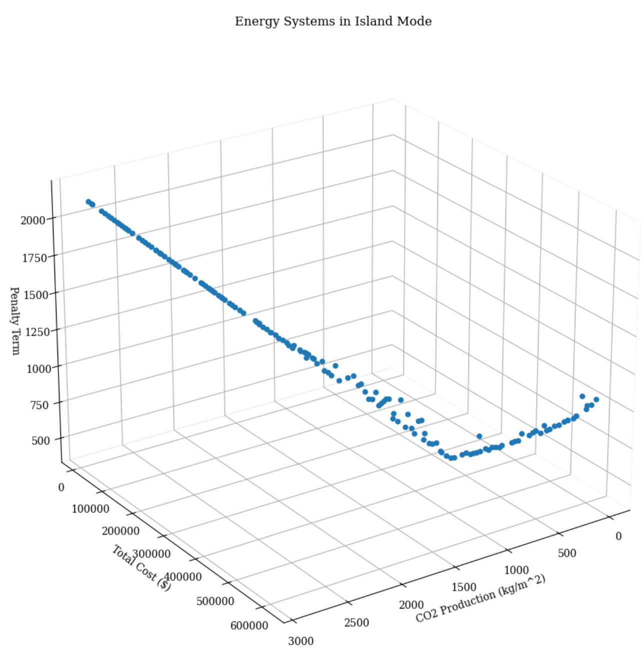

Figure 7: Pareto front of Island Mode using NSGA-II

Table 2: Optimization Points in Island Mode

N_{solar}	N_{wind}	N_{batt}	C_{total} **(€)**	$CO2_{total}$ **(kg)**	P_{Btotal}
494	88	400	619,500	0	1,062.81
500	41	400	386,355	600.405	451,886

These results underscore the intricate balance required in designing energy systems that are both sustainable and economically viable. The analysis demonstrates the effectiveness of MOO algorithms in identifying diverse solutions that cater to varying priorities of environmental impact and cost.

5.2 Analysis of Grid Mode Results

The Grid Mode analysis involves assessing the Pareto front generated by NSGA-II and NSGA-III algorithms, alongside specific optimization points that provide insight into the system's performance. The Pareto front for Grid Mode, as visualized in the provided figures, captures the multidimensional trade-off between CO2 emissions, total cost, and grid-supplied power.

In the optimization points table for Grid Mode, one row details a scenario with zero CO2 emissions, which would be positioned at the rightmost edge of the Pareto front, representing an environmentally optimal yet economically expensive solution. This is achieved with a configuration of 494 solar panels and 39 wind turbines, without the need for generators, thus not contributing to CO2 emissions, but resulting in a higher total cost of 361,7419k.

Another row in the table corresponds to a more cost-effective solution that matches the CO2 emissions level from the Island Mode, yet at a significantly reduced cost. This setup, involving 447 solar panels and 14 wind turbines, alongside a minimal use of generators, incurs CO2 emissions of 590.6691 kg, similar to the Island Mode. However, it benefits from a lower cost, totaling 202,1604k, demonstrating the economic advantages of the Grid Mode.

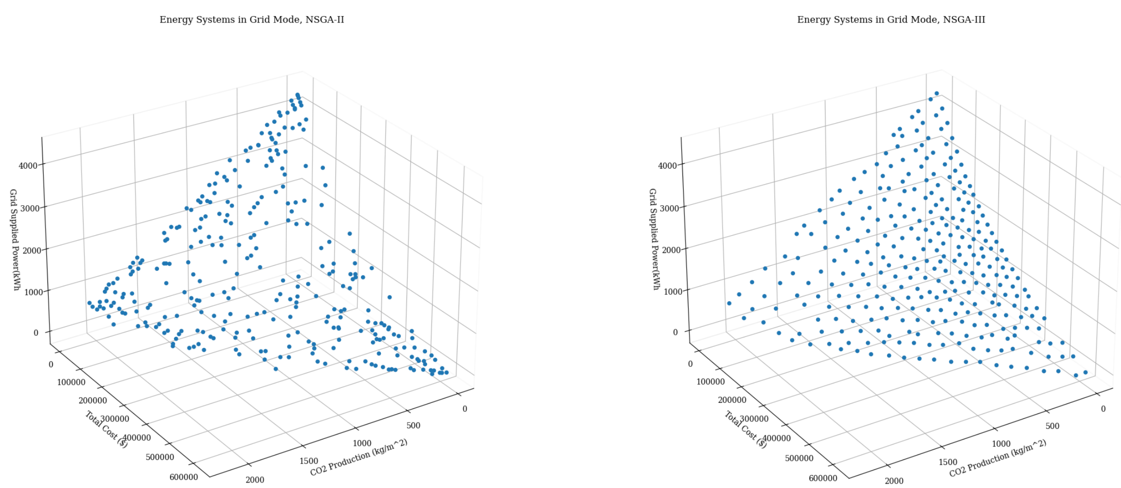

Figure 8: Left: Pareto front for the Grid Mode using NSGA-II algorithm. Right: Pareto front using NSGA-III algorithm.

Table 3: Optimization Points in Grid Mode

N_{solar}	N_{wind}	N_{batt}	N_{gen}	C_{total} **(€)**	$CO2_{total}$ **(kg)**	E_{grid} **(kWh)**
494	39	308	0	361,741.9	0	1,042.824
447	14	2	14	202,160.4	590.6691	1,383.281

This analysis indicates the potential for significant cost savings in Grid Mode when configured to match the CO2 emissions levels of the Island Mode, thus providing a compelling case for its adoption in scenarios where economic constraints are predominant.

6 Conclusions

Summary of Major Findings

This report presented a detailed examination of Multi-Objective Optimization (MOO) within the context of renewable energy systems, providing a primer on MOO concepts followed by their application in designing an optimized energy system for a university campus. Through the development of a robust mathematical model, the study showcased the potential of evolutionary algorithms in managing the trade-offs inherent in renewable energy system design, particularly emphasizing cost, CO2 emissions, and energy reliability.

The study underscores the potential of aligning energy consumption patterns of universities, research centers, and factories with the operational peaks of renewable energy systems. By focusing on facilities with energy demands that coincide with times of high renewable energy production, this approach presents a pragmatic step towards reducing the carbon footprint. This strategy not only capitalizes on the available renewable energy but also proposes a gradual transition away from fossil fuels, by first making these facilities self-sufficient, thereby easing the overall demand on traditional power grids.

Limitations and Directions for Future Research

The study's simulation, while insightful, was limited to a single day. A more robust approach would involve long-term simulations, potentially spanning the 25-year lifespan of an energy system, to account for the substantial benefits of feeding excess energy into the grid. Future iterations could incorporate yearly maintenance costs or return on investment as additional objective functions, providing a more comprehensive assessment of economic viability.

Moreover, introducing spatial constraints through an objective function for the required area could lead to innovations such as larger, more cost-intensive wind turbines that offer greater power output per square meter. The adoption of solar trackers could also be modeled to evaluate their impact on energy production versus their initial cost.

Enhancing the model with detailed considerations of maintenance equipment like inverters and rectifiers would bring the simulation closer to operational realities. Lastly, a granular analysis of the constants used, tailored to the specific geographic and climatic conditions of the site, would greatly refine the accuracy of the model.

Such advancements would not only improve the model's precision but also enrich the strategic planning of energy systems, contributing to more sustainable and economically sound energy solutions.

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