A Multi-Objective Approach for Optimizing Technical, Environmental, and Economic Impact of Energy Communities: A Case Study of a Residential Community in Tarragona

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ABSTRACT

In this paper, we introduce a novel framework tailored for the design and optimization of renewable energy communities (RECs) in residential areas, emphasizing a balance between techno-economic feasibility and environmental impact. Our approach focuses on determining the optimal design of configuration and sizing of renewable energy technologies, including photovoltaic systems, wind turbines, and battery electrical energy systems, guided by comprehensive criteria encompassing energy efficiency, cost-effectiveness, and environmental impact. We have developed a data-driven framework that merges the capabilities of Homer Pro with an in-house-developed Python tool to perform the calculations of environmental and economic factors. This framework integrates an advanced machine-learning algorithm and incorporates both life cycle cost (LCC) and life cycle assessment (LCA) in evaluating the REC model. Our model lies in establishing a multi-objective optimization model that not only strives to minimize LCC and LCA parameters but also aims to maximize the utilization of green energy. Additionally, this study is further reinforced by the incorporation of a Multi-Criteria Decision-Making (MCDM) approach through the Weighted Sum Model (WSM), which enables stakeholders to weigh their preferences regarding LCC, LCA, thereby facilitating the selection of a REC scenario that best aligns with their specific objectives. This represents an advancement in REC system planning, providing a nuanced and customizable tool for the residential sector to adopt sustainable energy solutions effectively. A case study of a residential community of 100 buildings in Tarragona, Spain, is used to demonstrate the framework application. The findings of our case study highlight significant economic and environmental benefits in REC design, showcasing an optimal solution that dramatically reduces the levelized cost of energy (LCOE) by 85% in comparison to the base case scenario with a payback period of 7.1 years for the minimum cost solution, along with a notable decrease in the environmental impact of 55% with a payback period of 12.5 years for the minimum environmental impact solution. In summary, this study provides a novel framework tool for stakeholders, facilitating informed decision-making in the integration of renewable energy communities within residential sectors, thereby paving the way for more sustainable energy communities.

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1 INTRODUCTION

The transition towards sustainable energy solutions is a global imperative, driven by the urgent need to address climate change and the increasing demand for environmentally friendly energy practices[1]. The building sector consumes a large amount of energy and natural resources, with negative impact on the environment. For instance, 50% of energy usage, 33% of water use, 50% of raw material extraction, and 40% of greenhouse gas emissions in Europe are attributed to buildings[2], [3]. The Sustainable Development Goals (SDGs) of the United Nations (UN) emphasize the necessity of addressing these effects and identify the construction industry as a critical participant in attaining environmental goals on a local and global scale [4].

Within this context, Renewable Energy Communities (RECs) represent a transformative approach to energy consumption and production, particularly in the residential sector. This paper presents a novel multi-objective approach designed to optimize the technical, environmental, and economic aspects of RECs in residential areas, with a focus on a case study from Tarragona, Spain. The integration of renewable energy sources, such as photovoltaic systems, wind turbines, and battery storage systems, into the energy mix of residential communities, offers a pathway to reduce greenhouse gas emissions and enhance sustainability. However, achieving an optimal balance between technological feasibility, economic viability, and environmental benefits poses significant challenges.

Several technical, economic, and environmental problems arise with the idea of an energy community. The integration of renewable energy resources requires the use of cutting-edge technology [5], such as smart grids[6], [7], energy storage systems[8], and demand response mechanisms[6].

Globally, Renewable Energy Communities (RECs) are gaining prominence with successful implementations in cities like Beijing, Wuhan, and Melbourne, and have become a focal point in European renewable energy discourse following the EU RED II Directive of 2018. The design and optimization of RECs involve selecting appropriate renewable energy sources, energy storage systems, and implementing energy-efficient building designs, considering factors such as community layout, local climate, and energy demand profiles to maximize resource utilization. Achieving an optimal energy mix that promotes economic and environmental sustainability requires sophisticated modeling techniques and optimization algorithms [9], [10].

In response to these challenges and opportunities, our research introduces a multi-objective approach that balances RECs' technical, environmental, and economic dimensions. By leveraging a data-driven framework that combines the modeling strength of Homer Pro with an in-house Python tool, that incorporates an in-house tool developed in Python programming language that integrates life cycle cost (LCC), life cycle assessment (LCA) calculations and machine learning models.

2 METHODOLOGY

Our methodology optimizes the Renewable Energy Community (REC) design in a residential area of Tarragona, Spain. The framework consists of five primary phases: renewable energy community modeling using Homer Pro software to design and generate scenarios [11], a Python in-house tool was used for sustainability parameters calculations, and also for machine learning model development , Pareto solutions/multi-objective optimization for economic and environmental objectives. and later multi-criteria decision-making to facilitate the selection according to the needs/preferences of stakeholders, as depicted in Figure 1.

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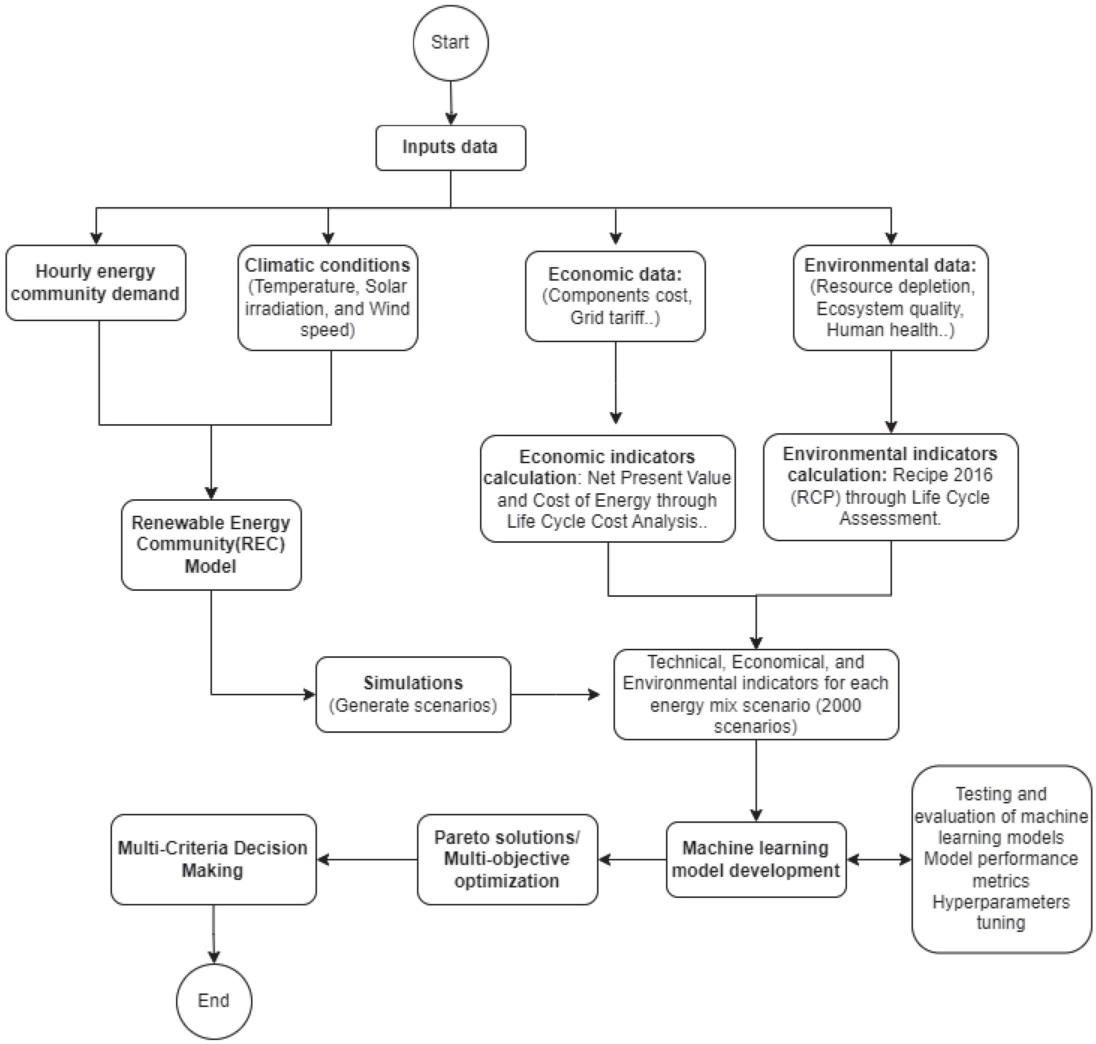

Figure 1: Framework for the renewable energy community system design optimization.

2.1 Energy System Modeling

Utilizing Homer Pro software, we model the REC to include a diverse mix of renewable energy technologies such as solar photovoltaic systems, wind turbines, and energy storage units. This phase generates a range of scenarios that align with the community's energy demands, detailed in a schematic representation in Figure 2. The energy system modeling phase sets the foundation for analyzing different energy mix configurations.

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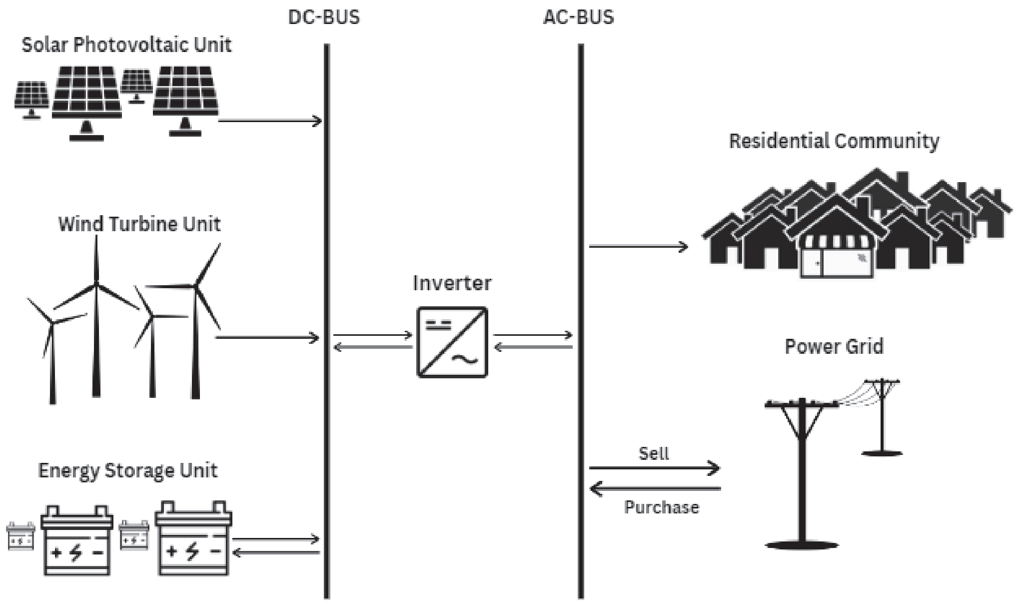

Figure 2: Schematic of the proposed renewable energy community system.

2.2 Sustainability Parameters Calculation

An in-house Python tool calculates key sustainability metrics, focusing on the economic and environmental performance of each energy scenario. This includes the application of life cycle cost (LCC) and life cycle assessment (LCA) methodologies to evaluate the long-term economic feasibility and environmental impact of the REC configurations.

2.3 Machine Learning Model Development

To navigate the complex interplay between different REC configurations and their sustainability outcomes, we train a Random Forest Regression model with data from 2000 feasible energy mix scenarios. This machine learning approach predicts the performance of each configuration against our sustainability criteria, facilitating the identification of optimal designs.

2.4 Multi-Objective Optimization

The training of a Random Forest Regression model using a dataset of 2000 scenarios for community-based renewable energy systems generated from the HOMER Pro software is the first step in the optimization process. This dataset includes several renewable energy system configurations together with the associated economic metrics (e.g. levelized cost of energy and net present cost) and environmental impact indicators (e.g. ReCiPe scores). Notably, Python was used to execute the LCA and LCC calculations, providing the essential economic and environmental indicators for the machine learning model's training.
The Random Forest Regression algorithm establishes a functional relationship between the system configurations used as input parameters and the economic metrics and environmental impact indicators utilized as output variables. Each tree in the Random Forest is constructed using a different subset of the training data and a random subset of features. The final prediction is then made by aggregating the predictions of all the individual trees in the forest. The dataset is provided to the model during training to assist it in identifying correlations and patterns between system parameters and related metrics. The model develops the capacity to predict the economic and environmental performance of various system

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configurations as a result of this training process. The inherent trade-offs between the cost of energy and environmental impact could be captured by the machine learning model, which leads to the enhancement of decision-making and design optimization.

2.5 Multi-Criteria Decision-Making (MCDM)

Finally, we employ a Multi-Criteria Decision-Making approach using the Weighted Sum Model (WSM) to align the REC design with stakeholder preferences. This phase enables the prioritization of objectives, such as cost reduction or environmental impact minimization, guiding the selection of the most appropriate REC scenario for implementation.

3 Case study

The planned renewable energy community, which will be implemented in a neighborhood of Tarragona, Spain with 100 buildings, will utilize key factors such as electrical demand, solar radiation, temperature, component costs, and energy prices for modeling in HOMER Pro software. An in-house Python tool was used to collect real-time hourly electricity consumption data from the residential sector via the Datadis platform (i.e., this platform provides extensive access to hourly electricity consumption data in Spain). Daily and seasonal usage patterns are shown in Figure 3, with an average daily use of 691.34 kWh and a peak demand of 70.35 kW.

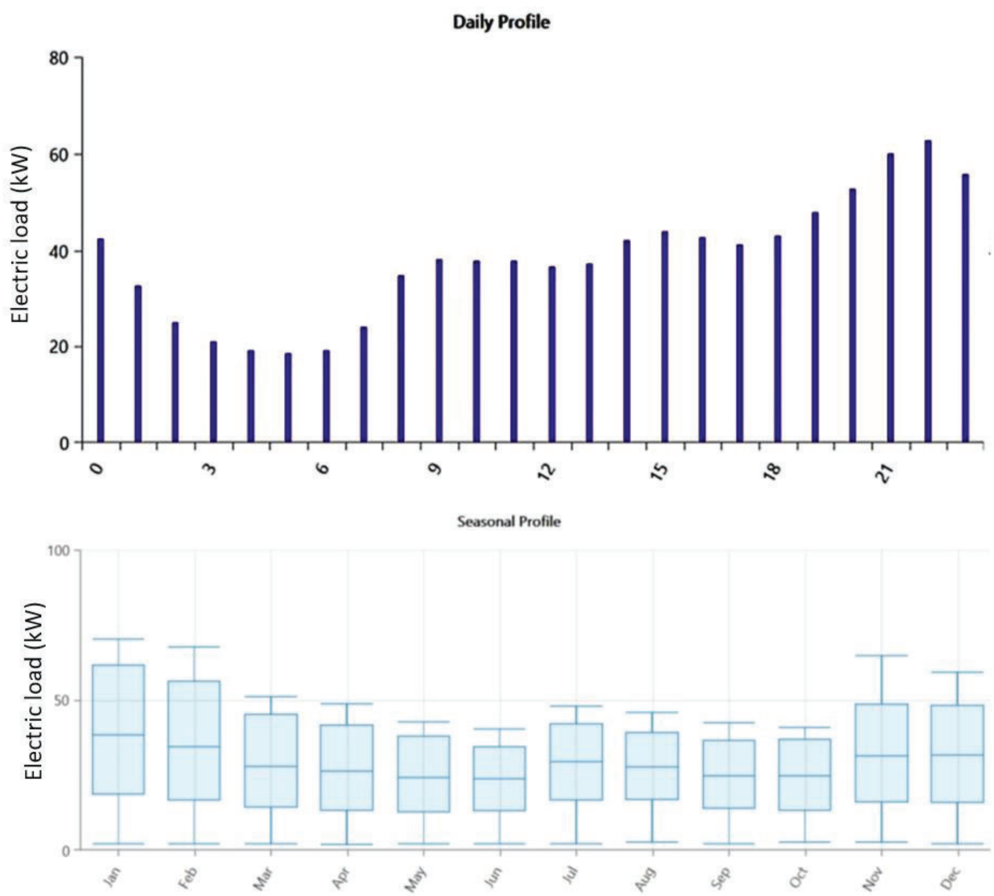

Figure 3: Electricity demand daily (top figure) and seasonal (bottom figure) profiles for a 100-building residential energy community in Tarragona, Spain.

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Climatic data specifically for our REC case study were collected from a meteorological station situated within Tarragona. This collected dataset, which encompasses variables such as wind speed, ambient temperature, and solar irradiance, was processed and formatted for integration into the Homer Pro software. The average monthly values for various climate variables are shown in Figure 4.

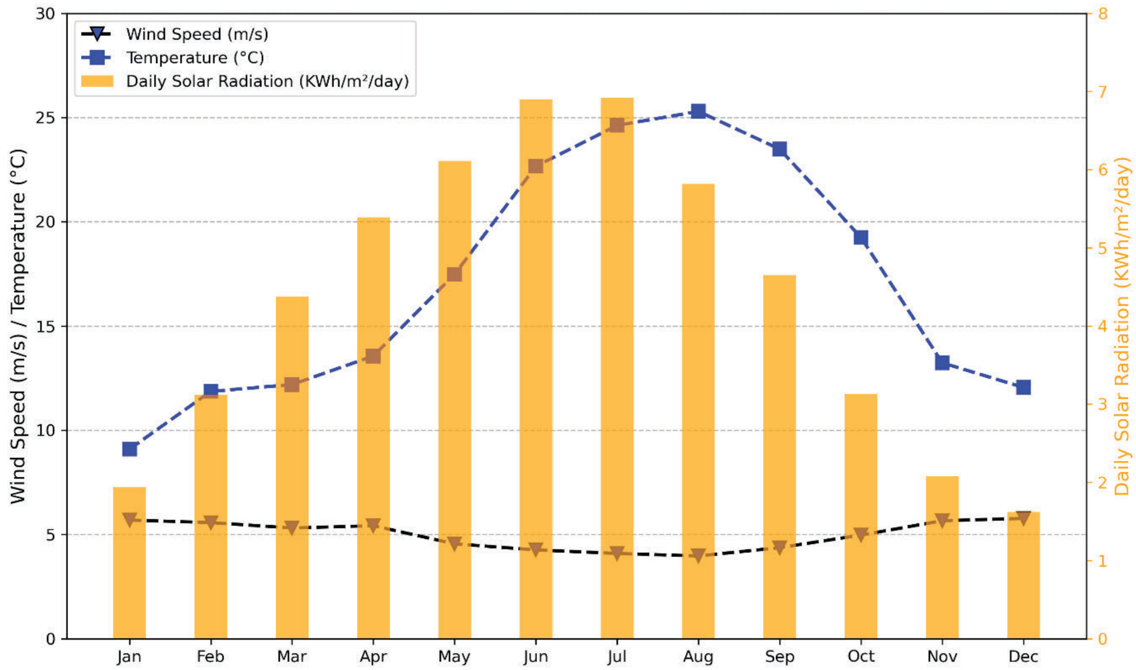

Figure 4: Climatic Data for the Renewable Energy Community in Tarragona, Spain.

4 Results

The findings of this study are divided into two primary sections. Initially, the research evaluates the efficiency of various REC sizes within an optimization framework, employing a specially developed Machine Learning model that considers both environmental and economic factors. The objective here is to enhance the REC's viability by fine-tuning the design elements of the solar PV system, wind turbines, and battery storage system. Subsequently, the study demonstrates the REC's optimal configuration by incorporating multi-objective optimization, or Pareto solutions, alongside multi-criteria decision-making methods to support the decision-making process. This holistic approach facilitates a thorough assessment and fosters informed decision-making for the REC.

Figures 5 and 6 employ parallel coordinate plots to elucidate the interconnections among design parameters—namely, capacities for photovoltaic systems (PV), wind turbines (WT), and battery electrical energy storage (BEES)—and key performance indicators such as the ReCiPe 2016 aggregated impact factor (RCP) and the levelized cost of energy (LCOE) across diverse energy mix scenarios. These plots visually map the spectrum and intensity of LCOE values (Figure 5) and environmental impacts (Figure 6), using a color gradient to signify varying LCOE levels, with the corresponding color legend provided. This method offers a vivid depiction of how different configurations affect both cost efficiency and environmental footprint, guiding stakeholders through the decision-making process by highlighting the trade-offs and synergies between economic and environmental optimization.

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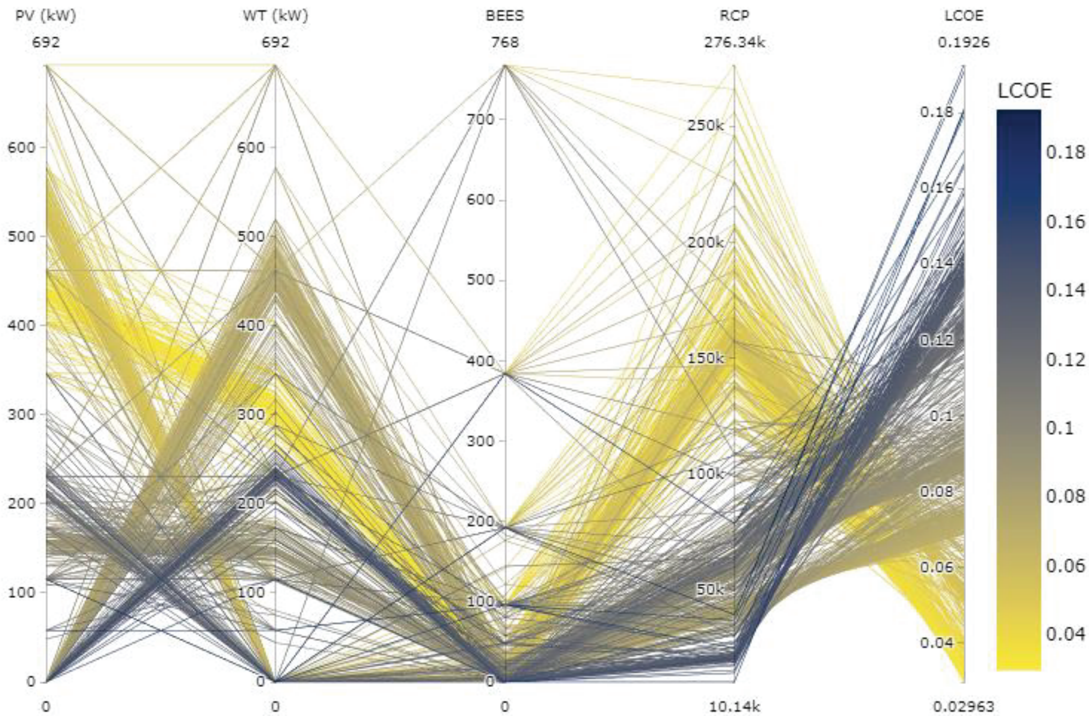

Figure 5: Parallel coordinate plot: design parameters and targets analysis for LCOE optimization.

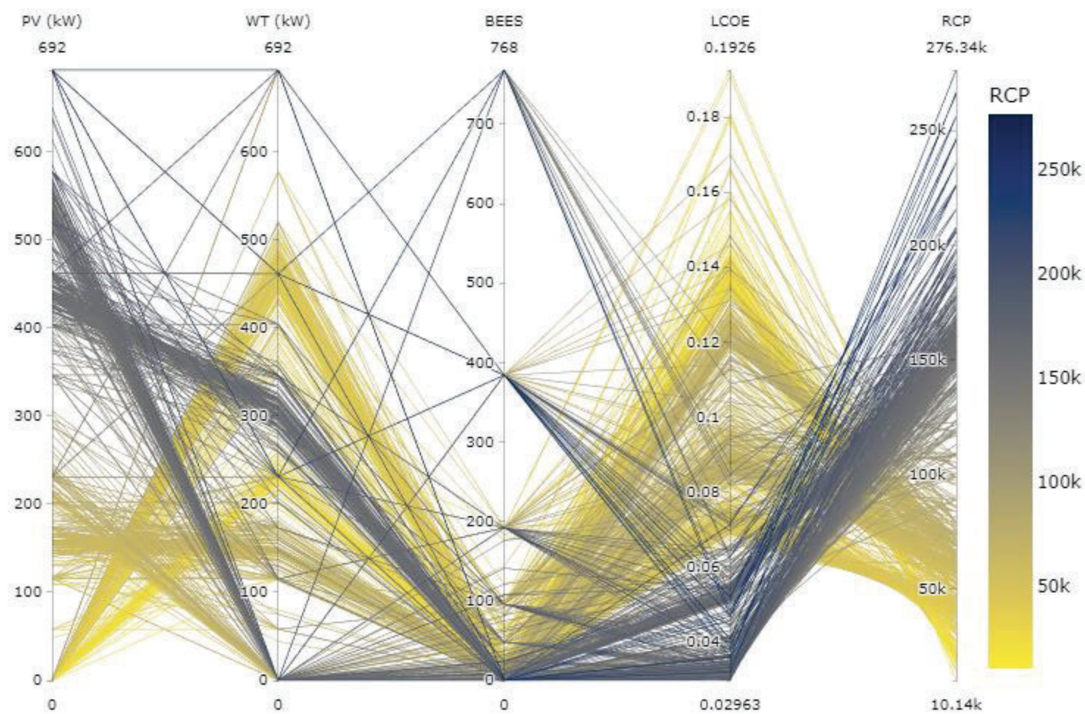

Figure 6: Parallel coordinate plot: design parameters and targets analysis for RCP optimization.

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In detail, the parallel coordinate plots in Figures 5 and 6 reveal significant insights into the optimization of energy mixes. For instance, scenarios yielding the lowest LCOE tend to favor higher PV capacities, underscoring its role in reducing costs. On the other hand, scenarios aimed at minimizing environmental impacts demonstrate a balanced approach to allocating PV and WT capacities, suggesting that a diversified renewable energy portfolio is crucial for achieving environmental targets. Additionally, these figures facilitate a deeper understanding of how shifts in design parameters can influence overall project outcomes, enabling stakeholders to make choices that align with their strategic goals and sustainability criteria. Through these visual comparisons, decision-makers can identify the configurations that offer the most cost-effective or environmentally friendly solutions, thereby informing the selection of the optimal energy mix.

Figure 7 illustrates the application of Multi-Objective Optimization for selecting the optimal scenario through Pareto Sets Analysis. This figure highlights the balance between two objectives: the Levelized Cost of Energy (LCOE) and its environmental footprint measured by RCP across all possible solutions. It also demonstrates the impact of assigning equal importance to both objectives (balanced weight = 0.5), resulting in a notable decrease in environmental impact for a minimal increase in cost. The base scenario depicted is the current state, where energy is solely sourced from the grid. Moreover, Figure 7 provides valuable insights for decision-making by distinctly displaying the Pareto optimal solutions for different weighting schemes.

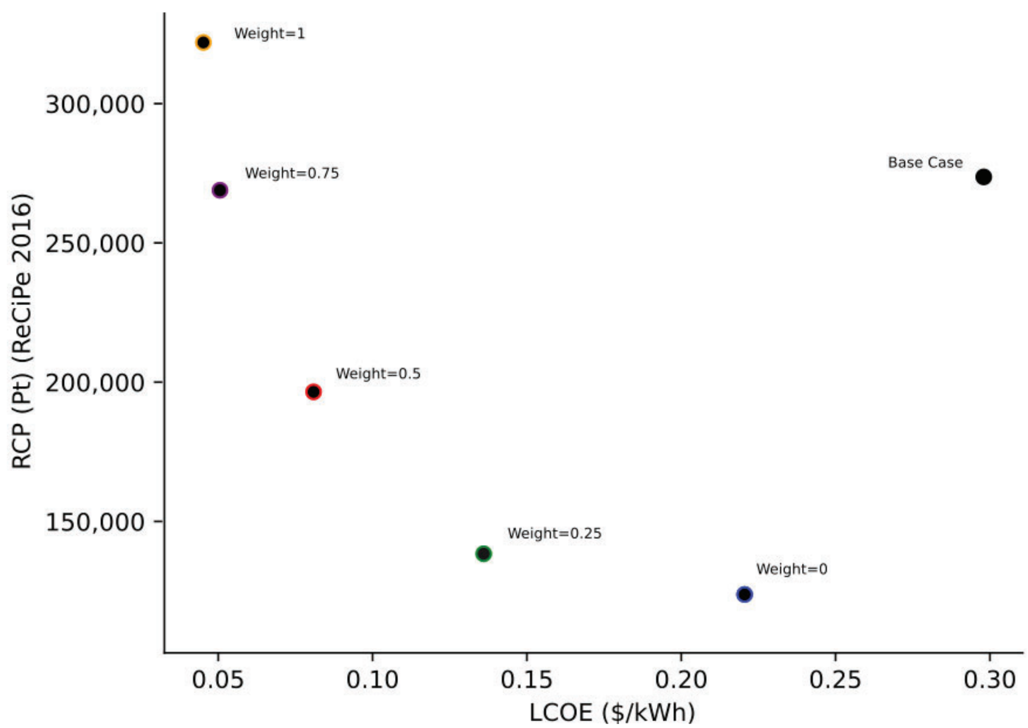

Figure 7: Multi-Objective Optimization for Optimal Scenario Selection: Pareto Sets Analysis

The findings from the multi-objective optimization elucidate the inherent compromises between the Levelized Cost of Energy (LCOE) and the environmental footprint. Through an analytical comparison of diverse scenarios, marked variations in LCOE and Environmental Impact (as quantified by RCP) are observed. The analysis reveals a pronounced escalation in LCOE by approximately 396.64 % when compared to the scenario with the lowest cost against that with the minimal environmental impact, which concurrently achieves a substantial diminution in environmental impact by 61.65%. Moreover, the divergence in LCOE between the cost-minimized and equilibrium solutions stands at 44.66%, with

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the environmental impact of the latter augmenting by nearly 55.75 %. In contrast to the baseline scenario, the option prioritizing minimal environmental impact exhibits a reduction in LCOE by about 25.95%, indicating enhanced economic efficiency while prioritizing environmental sustainability. This scenario also manifests a 9.89 % elevation in environmental impact over the standard scenario, suggesting a minimized ecological footprint. A comparison between the baseline and the cost-minimized solution delineates an 85.04% reduction in LCOE, albeit at the expense of a 18.71 % increase in environmental impact. The equilibrium solution further highlights the feasibility of achieving cost reductions, with a significant LCOE decrease of roughly 72.86 % compared to the baseline scenario, despite a 27.02 % increase in environmental impact. These comparative analyses underscore the utility of multi-objective optimization in facilitating strategic trade-offs and enhancements relative to the baseline scenario. Complementing Figure 7, Figure 8 provides detailed insights into the capacity allocations for Photovoltaic (PV), Wind Turbine (WT), and Battery Electrical Energy Storage (BEES) across different weighting configurations, thereby illustrating the impact of weighting on technological capacity deployment.

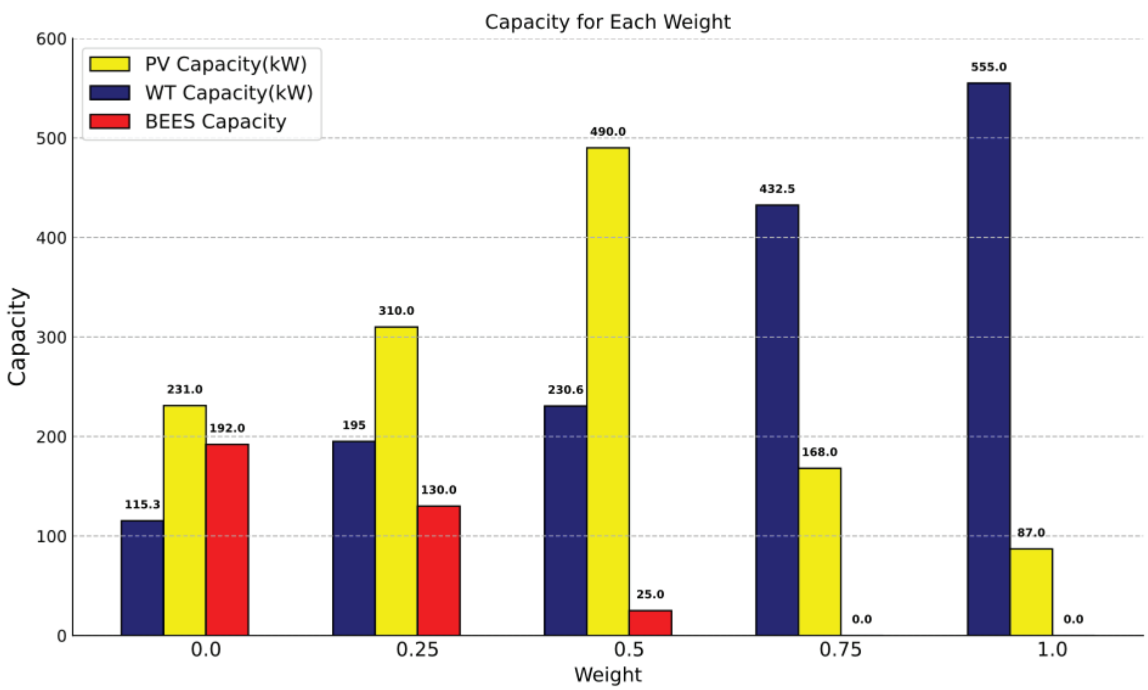

Figure 8: Comparative Evaluation of Energy Source Capacities Across Different Weightings.

As shown in Figure 8, the min impact solution (weight=0), the focus is to get the optimal energy mix scenario that minimizes the impact on the environment; in this energy mix scenario, we have a relatively balanced capacity allocation among the PV, WT, and BEES reflects a strategy that aims to reduce the overall environmental footprint. The capacity installed for each technology is given as follows: PV (115.3 kW), WT (231 kW), and BEES (192 units); this is a moderately balanced approach towards utilizing multiple renewable energy sources while considering the environmental consequences. Moving to the intermediate solution (weight=0.5), in this solution, the aim is to get the optimal energy mix scenario by balancing the economic benefits and the environmental impact; this energy mix scenario, compared to min impact solution, showcases an increase in the PV and WT capacities by approximately 69.30 % (195kW), 112.55 % (310 kW), respectively. However, the BEES capacity decreases from the min impact solution (192 units) to the intermediate solution (25 units) by 86.98%. Lastly, the main objective of the min cost solution (weight=1) is to get the most cost-effective energy mix by minimizing the LCOE. In this scenario, the PV capacity has a higher capacity of 555 kW; this

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represents an increase of 184.62 % and 381.56 % compared to the balanced and min impact solutions, respectively. The min-cost solution has a lower WT capacity of 87 kW.

This decrease represents 82.45 % and -62.81% compared to the balanced and min impact solutions, respectively. These comparisons emphasize the variation in capacity installed through different solutions; the minimum cost solution highlights cost effectiveness, leading to a higher PV capacity while a lower WT capacity and no energy storage. The Balanced solution strives for a balanced approach with a large WT capacity and modest PV and energy storage capacities. The minimum impact approach prioritizes reducing the impact on the environment, leading to a balanced capacity distribution across all technologies.

In essence, the selection within energy mix scenarios depends on specific goals. For cost-efficiency, PV stands out due to its lower LCOE but higher environmental impact than WT. Conversely, WT is preferred for reducing environmental footprints. BEES sees moderate use across scenarios, highlighting the balance between cost, sustainability, and technology characteristics in renewable energy designs.

The outcomes of this study, influenced by factors like location, resource availability, and local conditions, suggest that applying the same framework to another case might yield different results.

5 CONCLUSIONS

In this study, we introduced a multi-objective approach for optimizing renewable energy communities (RECs) by integrating photovoltaic systems, wind turbines, and battery storage, guided by energy, economic, and environmental considerations. Utilizing Homer Pro and an inhouse Python tool that incorporates machine learning alongside life cycle cost (LCC) and life cycle assessment (LCA), our goal was to minimize LCC and LCA while maximizing the use of green energy. The research revealed that the minimum environmental impact solution achieved a 25.95 % reduction in the levelized cost of energy (LCOE) to \$0.220/kWh and a decrease in environmental impact, as measured by RCP, to 1.242 105 Pts. Conversely, the balanced solution offered a significant drop in LCOE by 72.86 % to \$0.080/kWh but resulted in a 27.02 % increase in environmental impact. Meanwhile, the minimum cost solution showed an 85.04 % reduction in LCOE to \$0.044/kWh, with an 18.32 % higher environmental impact. This illustrates the trade-offs between cost reduction and environmental impact in REC optimization. The study not only provides a comprehensive methodology for REC system sizing but also underscores the pivotal role of PV capacity in enhancing REC cost-effectiveness. Ultimately, this approach serves as an effective planning tool for integrating RECs into existing energy communities, balancing techno-economic efficiency and environmental sustainability.

NOMENCLATURE

ANN	Artificial Neural Network
BEES	Battery Electrical Energy Storage
CC	Capital cost
HOMER	Hybrid Optimization Model for Electric Renewables
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LCIA	Life Cycle Impact Analysis
LCOE	Levelized Cost of Energy
MAE	Mean Absolute Error
ML	Machine Learning
MOO	Multi-Objective Optimization
MCDM	Multi-Criteria Decision-Making
NPC	Net Present Cost
O&M	Operation and Maintenance
PV	Photovoltaics
REC	Renewable Energy Community

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RESs	Renewable Energy Sources
RCP	ReCiPe 2016 aggregated impact factor (Pts)
WT	Wind Turbine
WSM	Weighted Sum Model

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