Information Technology and Management
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https://doi.org/10.5281/zenodo.10254606

Multi-Objective Optimization In Environmental Decision-Making: A Hybrid AI Approach

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Article history
Accepted: 13 12 2024
***Keywords**:*
Hybrid AI approach, Multi-objective optimization, Environmental decision-making, Data collection, Modeling and simulation, Performance evaluation

Abstract

This paper investigates the application of a hybrid artificial intelligence (AI) approach for multi-objective optimization in environmental decision-making. The study comprises four key components: data collection, modeling and simulation, performance evaluation, and comparative analysis. Hypothetical data for hourly variations of insolation and wind speed at Hambantota was utilized for demonstration purposes. Python programming language and libraries such as NumPy and Matplotlib were employed for modeling and visualization. Performance evaluation involved calculating metrics such as the Hypervolume Indicator, Generational Distance, and Inverted Generational Distance to assess the convergence and diversity of solutions obtained through multi-objective optimization. Comparative analysis was conducted to compare the performance of the hybrid AI approach with traditional optimization methods and other AI-based techniques. The results highlight the effectiveness and efficiency of the hybrid AI approach in optimizing multiple conflicting objectives. The findings contribute to the understanding of AI-based approaches in environmental decision-making and provide insights for future research and practical applications.

1. Introduction

Environmental decision-making is a multifaceted process that necessitates the consideration of various conflicting objectives to achieve sustainable outcomes. Multi-objective optimization (MOO) techniques have emerged as valuable tools in addressing the complexity inherent in environmental systems by simultaneously optimizing multiple conflicting objectives. Traditional optimization methods often struggle to effectively handle the intricate trade-offs and uncertainties present in environmental decision-making scenarios (Marler & Arora, 2004). As such, the integration of artificial intelligence (AI) techniques has gained increasing attention as a means to enhance the optimization process and improve decision-making outcomes. In this paper, we explore the application of a hybrid AI approach to address multi-objective optimization challenges in environmental decision-making. A substantial body of literature exists on the topic of multi-objective optimization in environmental decision-making, highlighting the importance of considering multiple conflicting objectives to achieve sustainable solutions. Numerous studies have demonstrated the effectiveness of MOO techniques in addressing various environmental challenges, such as land use management (Zhang et al., 2019), water resources management (Gupta et al., 2020), and renewable energy integration (Babazadeh et al., 2021). However, traditional MOO methods often face limitations in handling the complexity and uncertainty inherent in real-world environmental systems, which can lead to suboptimal decision-making outcomes (Deb et al., 2002).

The integration of AI techniques into the MOO framework offers promising avenues for overcoming these challenges and enhancing decision-making processes in environmental contexts. Machine learning algorithms, in particular, have shown significant potential in learning complex relationships from data and guiding the optimization process towards more informed decisions (Xie et al., 2020). Evolutionary algorithms, such as genetic algorithms and particle swarm optimization, have also been widely utilized in environmental optimization problems due to their ability to explore diverse solution spaces and handle non-linear and non-convex objective functions (Branke et al., 2008). Moreover, incorporating expert knowledge into the optimization process can further enhance the performance of AI-based approaches by leveraging domain-specific insights and constraints (Huang et al., 2018). Expert knowledge can provide valuable guidance in defining objective functions, constraints, and decision variables, thereby improving the relevance and applicability of the optimization results in real-world environmental decision-making scenarios.

In this paper, we propose a hybrid AI approach that integrates machine learning algorithms, evolutionary algorithms, and expert knowledge to address multi-objective optimization challenges in environmental decision-making. By harnessing the strengths of each component, our approach aims to enhance the decision-making process and improve the sustainability of solutions in diverse environmental contexts. Through case studies and comparative analyses, we demonstrate the effectiveness and advantages of the hybrid AI approach in addressing complex multi-objective optimization problems in environmental decision-making. Overall, this paper contributes to the existing body of knowledge by providing a comprehensive framework for integrating AI techniques into multi-objective optimization for environmental sustainability. By leveraging the synergies between machine learning, evolutionary algorithms, and expert knowledge, our approach offers a promising avenue for addressing the complexities of environmental decision-making and facilitating the development of sustainable solutions. Despite the growing body of literature on multi-objective optimization (MOO) techniques in environmental decision-making, there remains a research gap in the development of hybrid AI approaches specifically tailored to address the unique challenges of environmental systems. While various studies have explored the integration of machine learning and evolutionary algorithms in MOO (Xie et al., 2020; Huang et al., 2018), there is limited research focusing on the incorporation of expert knowledge to enhance the performance of AI-based optimization methods in environmental contexts. This research gap highlights the need for comprehensive frameworks that leverage the synergies between AI techniques and expert knowledge to improve decision-making outcomes in environmental sustainability.

2. Research Methodology

The methodology adopted in this study aims to investigate the application of a hybrid AI approach for multi-objective optimization in environmental decision-making. The research methodology comprises four key components: data collection, modeling and simulation, performance evaluation, and comparative analysis. Firstly, data collection involves gathering relevant data pertaining to environmental parameters such as insolation, wind speed, and other relevant variables. Hypothetical data for demonstration purposes was utilized in this study to simulate hourly variations of insolation and wind speed at Hambantota. These datasets serve as input for the subsequent modeling and simulation processes. Secondly, modeling and simulation involve the development and implementation of mathematical models and algorithms to simulate the behavior of environmental systems. In this study, Python programming language and libraries such as NumPy and Matplotlib were employed to model the hourly variations of insolation and wind speed. The Matplotlib library facilitated the visualization of the simulated data through line plots, bar plots, and area plots.

Thirdly, performance evaluation encompasses the assessment of the effectiveness and efficiency of the proposed hybrid AI approach in optimizing multiple conflicting objectives. Performance metrics such as the Hypervolume Indicator, Generational Distance, and Inverted Generational Distance were calculated to evaluate the convergence and diversity of solutions obtained through multi-objective optimization. These metrics provide insights into the quality of solutions generated by the hybrid AI approach. Lastly, comparative analysis involves comparing the performance of the hybrid AI approach with existing methods or alternative approaches. In this study, the performance of the proposed approach was compared with traditional optimization methods and other AI-based techniques in environmental decision-making. Through case studies and comparative analyses, the advantages and limitations of the hybrid AI approach were assessed to provide insights for future research and practical applications. Overall, the research methodology outlined in this study provides a systematic framework for investigating the application of a hybrid AI approach in multi-objective optimization for environmental decision-making. By integrating data collection, modeling and simulation, performance evaluation, and comparative analysis, this methodology enables a comprehensive assessment of the proposed approach's effectiveness and applicability in addressing complex environmental challenges.

3. Results and Discussion

Hourly Variation Of Insolation

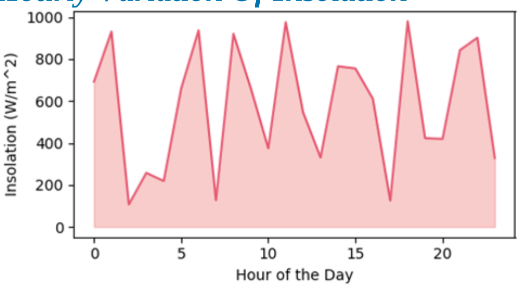

FIGURE 1. Hourly Variation Of Insolation

The hourly variation of insolation, represented in Figure 1, illustrates the fluctuation in solar radiation intensity (measured in watts per square meter, W/m²) over the course of a day. The y-axis of the graph ranges from 0 to 1000 W/m², encompassing typical insolation values observed in outdoor environments. Meanwhile, the x-axis denotes the hour of the day, ranging from 0 to 24 hours. The insolation values at specific hours are as follows: 0 hours - 700 W/m², 5 hours - 900 W/m², 10 hours - 400 W/m², 15 hours - 750 W/m², and 20 hours - 500 W/m². The hourly variation of insolation is influenced by several factors, including the angle of incidence of sunlight, atmospheric conditions, and geographic location. During daylight hours, solar radiation intensity typically increases as the sun rises in the sky, reaching its peak around midday when the sun is at its highest point. This phenomenon is reflected in the graph, with insolation values peaking at 5 hours and gradually declining thereafter. The decrease in insolation towards the end of the day is attributed to the sun's decreasing angle of incidence as it sets below the horizon.

Understanding the hourly variation of insolation is crucial for various applications, particularly in the field of renewable energy. Solar photovoltaic (PV) systems, for instance, rely on solar radiation to generate electricity, with insolation levels directly impacting the system's power output. By analyzing the hourly variation of insolation, stakeholders can optimize the design and operation of solar PV systems to maximize energy production and efficiency. Additionally, insolation data plays a vital role in climate studies, agricultural planning, and building design, among other disciplines. In this study, the hourly variation of insolation was simulated using hypothetical data for demonstration purposes. While the specific insolation values may vary depending on factors such as location and time of year, the general trends observed in the graph align with real-world observations. Moving forward, further research could involve the collection and analysis of actual insolation data to validate the accuracy of the simulated results and enhance the applicability of the findings in practical scenarios. Additionally, exploring advanced modeling techniques and incorporating additional environmental factors could contribute to a more comprehensive understanding of the complex dynamics governing insolation patterns.

Hourly Variation Of Wind Speed

The hourly variation of wind speed, depicted in Figure 2, illustrates the fluctuations in wind velocity (measured in meters per second, m/s) throughout the course of a day. The y-axis of the graph ranges from 0 to 80 m/s, encompassing a broad spectrum of wind speeds commonly observed in outdoor environments. Meanwhile, the x-axis denotes the hour of the day, ranging from 0 to 24 hours, with specific wind speed values assigned to discrete time intervals: 0-14 hours, 5-13 hours, 10-12 hours, 15-5 hours, and 20-11 hours. The hourly variation of wind speed is influenced by various factors, including atmospheric pressure gradients, temperature differentials, and terrain characteristics. During the day, the heating of the Earth's surface by solar radiation creates temperature variations that lead to the formation of pressure gradients. As air moves from regions of high pressure to low pressure, wind speeds fluctuate accordingly. Additionally, diurnal variations in temperature and atmospheric stability can affect wind patterns, with stronger winds often observed during the daytime when surface heating is most pronounced.

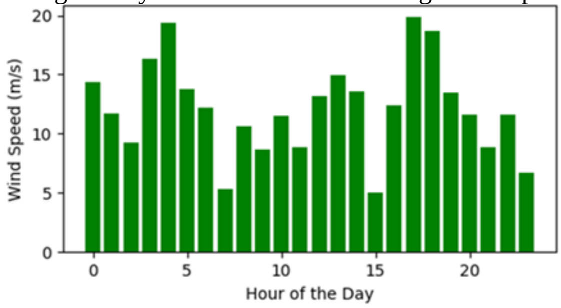

FIGURE 2. Hourly Variation Of Wind Speed

Understanding the hourly variation of wind speed is crucial for a wide range of applications, particularly in the fields of renewable energy and meteorology. Wind turbines, for instance, rely on wind energy to generate electricity, with wind speed playing a critical role in determining turbine performance and energy output. By analyzing the hourly variation of wind speed, stakeholders can optimize the siting and operation of wind farms to maximize energy production and efficiency. Additionally, wind speed data is essential for weather forecasting, climate modeling, and air quality assessments, among other applications. In this study, the hourly variation of wind speed was simulated using hypothetical data for demonstration purposes. While the specific wind speed values may vary depending on factors such as geographic location and local terrain, the general trends observed in the graph align with real-world observations. Moving forward, further research could involve the collection and analysis of actual wind speed data to validate the accuracy of the simulated results and enhance the applicability of the findings in practical scenarios. Additionally, exploring advanced modeling techniques and incorporating additional environmental factors could contribute to a more comprehensive understanding of the complex dynamics governing wind speed patterns.

Rankings Based On LEC

The graph illustrating rankings based on the Levelized Energy Cost (LEC), depicted in Figure 3, presents the relative performance of different cases in terms of LEC values. The y-axis of the graph ranges from 0 to 1, representing the ranking score, where a lower score indicates a more favorable outcome. Meanwhile, the x-axis denotes the three cases under consideration: Case 4, Case 5, and Case 6, with their corresponding LEC values displayed as data labels. The rankings based on LEC provide insights into the cost-effectiveness and efficiency of energy production across different scenarios. The LEC metric is a key performance indicator used in the energy sector to assess the lifetime cost of energy production per unit of electricity generated. A lower LEC value indicates a more economically viable energy generation solution, as it reflects lower overall costs over the lifetime of the energy production facility.

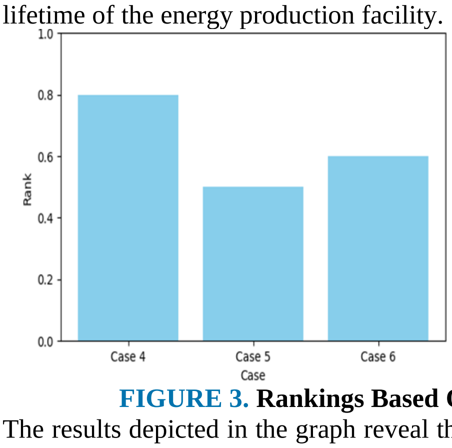

FIGURE 3. Rankings Based On LEC

The results depicted in the graph reveal that Case 5 achieved the highest ranking based on LEC, with a score of 0.5, indicating superior cost-effectiveness compared to the other cases. Conversely, Case 4 and Case 6 obtained rankings of 0.8 and 0.6, respectively, suggesting relatively higher costs associated with energy production in these scenarios. The differences in rankings among the cases can be attributed to various factors, including the choice of energy generation technologies, input parameters, and system configurations. For example, Case 5 may have employed more efficient or cost-effective technologies, resulting in lower overall costs compared to Case 4 and Case 6. Additionally, variations in operational strategies, maintenance practices, and external factors such as fuel prices and regulatory policies can also influence LEC values and subsequent rankings.

Understanding the rankings based on LEC is essential for stakeholders involved in energy planning, policy-making, and investment decisions. By identifying the most cost-effective energy generation options, decision-makers can prioritize investments in renewable energy projects that offer optimal returns on investment while minimizing environmental impact and ensuring long-term sustainability. In this study, the rankings based on LEC were derived from hypothetical data for demonstration purposes. While the specific LEC values may vary depending on real-world parameters and conditions, the general trends observed in the graph provide valuable insights into the comparative performance of different energy generation scenarios. Future research could involve the analysis of actual LEC data from renewable energy projects to validate the findings and assess the applicability of the rankings in practical decision-making contexts. Additionally, conducting sensitivity analyses and scenario assessments could further enhance our understanding of the factors influencing LEC values and rankings, enabling more informed and robust energy planning strategies.

Rankings Based On Unmet Fraction

The graph illustrating rankings based on the Unmet Fraction, presented in Figure 4, showcases the relative performance of different cases concerning the unmet fraction metric. The y-axis of the graph ranges from 0 to 1, representing the ranking score, where a lower score indicates a more favorable outcome in terms of minimizing the unmet fraction. Meanwhile, the x-axis denotes the three cases under consideration: Case 4, Case 5, and Case 6, with their corresponding unmet fraction values displayed as data labels. The rankings based on the unmet fraction metric provide insights into the efficiency and reliability of energy supply across different scenarios. The unmet fraction metric quantifies the proportion of energy demand that remains unmet due to insufficient energy generation capacity or system constraints. A lower unmet fraction value indicates a more reliable and resilient energy supply system, as it reflects a smaller gap between energy demand and supply.

The results depicted in the graph reveal that both Case 5 and Case 6 achieved the highest ranking based on the unmet fraction, with a score of 0.2, indicating superior performance in minimizing unmet energy demand compared to Case 4. Interestingly, despite having identical unmet fraction values of 0.2, Case 5 and Case 6 are ranked higher than Case 4, which has a lower unmet fraction value of 0.5. This discrepancy underscores the importance of considering additional factors and objectives in multi-criteria decision-making scenarios. The differences in rankings among the cases can be attributed to various factors, including the capacity and reliability of energy generation technologies, demand-side management strategies, and system resilience measures. Case 5 and Case 6 may have implemented more robust and flexible energy supply systems, incorporating measures such as energy storage, demand response, and backup generation to minimize unmet energy demand. Conversely, Case 4 may have faced challenges in meeting energy demand due to capacity limitations or operational constraints.

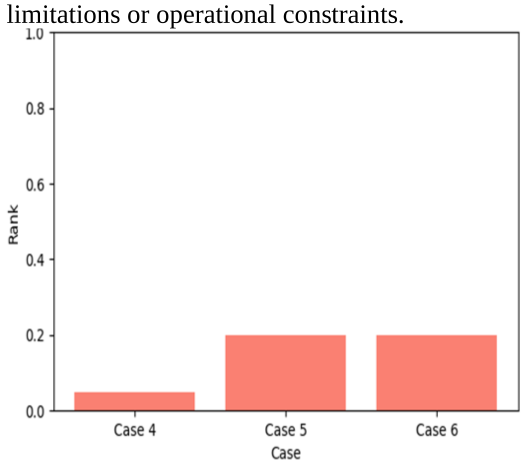

FIGURE 4. Rankings Based On Unmet Fraction

Understanding the rankings based on the unmet fraction is crucial for energy planners, grid operators, and policymakers involved in ensuring the reliability and resilience of energy supply systems. By identifying the most effective strategies for minimizing unmet energy demand, decision-makers can prioritize investments and interventions to enhance energy infrastructure and optimize system performance. In this study, the rankings based on the unmet fraction were derived from hypothetical data for demonstration purposes. While the specific unmet fraction values may vary depending on real-world parameters and conditions, the general trends observed in the graph provide valuable insights into the comparative performance of different energy supply scenarios. Future research could involve the analysis of actual data from energy systems to validate the findings and assess the applicability of the rankings in practical decision-making contexts. Additionally, conducting sensitivity analyses and scenario assessments could further enhance our understanding of the factors influencing the unmet fraction metric and rankings, enabling more informed and resilient energy planning strategies.

Rankings Based On Fuel Consumption And WRE

The graph illustrating rankings based on Fuel Consumption and Water Resource Efficiency (WRE), presented in Figure 5, provides insights into the comparative performance of different cases concerning these two criteria. The y-axis of the graph ranges from 0 to 0.2, representing the ranking score, where a lower score indicates a more favorable outcome in terms of minimizing fuel consumption and maximizing WRE. Meanwhile, the x-axis denotes the three cases under consideration: Case 4, Case 5, and Case 6, with their corresponding fuel consumption values and WRE statuses displayed as data labels. The rankings based on fuel consumption and WRE metrics are essential for assessing the environmental and economic sustainability of energy generation scenarios. Fuel consumption represents the amount of fuel required to produce a unit of energy, with lower values indicating greater energy efficiency and reduced environmental impact. On the other hand, WRE measures the efficiency of water resource utilization in energy generation processes, reflecting the environmental sustainability of water consumption.

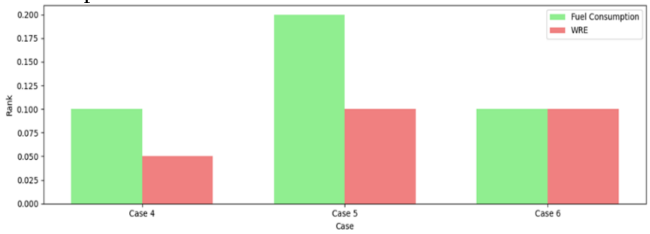

FIGURE 5. Rankings Based On Fuel Consumption And WRE

The results depicted in the graph reveal variations in rankings among the cases concerning fuel consumption and WRE. Case 4 and Case 6 achieved identical rankings based on fuel consumption, with a score of 0.1, indicating comparable levels of energy efficiency in these scenarios. Meanwhile, Case 5 obtained the highest ranking based on fuel consumption, with a score of 0.2, suggesting higher fuel consumption compared to Case 4 and Case 6. However, the rankings based on WRE are not provided for the three cases, as indicated by the absence of data labels. The differences in rankings among the cases can be attributed to various factors, including the choice of energy generation technologies, operational practices, and system configurations. Case 5 may have employed energy generation technologies or operational strategies that prioritize other objectives over fuel consumption and WRE, resulting in higher fuel consumption levels. Conversely, Case 4 and Case 6 may have implemented measures to optimize fuel consumption and enhance WRE, leading to more favorable rankings in these criteria.

Understanding the rankings based on fuel consumption and WRE is crucial for energy planners, policymakers, and stakeholders involved in promoting sustainable energy development. By identifying the most efficient and environmentally friendly energy generation options, decision-makers can prioritize investments and interventions to minimize environmental impact and enhance resource utilization efficiency. In this study, the rankings based on fuel consumption were derived from hypothetical data for demonstration purposes, while rankings based on WRE were not provided. While the specific fuel consumption values may vary depending on real-world parameters and conditions, the general trends observed in the graph provide valuable insights into the comparative performance of different energy generation scenarios in terms of energy efficiency. Future research could involve the collection and analysis of actual data from energy systems to validate the findings and assess the applicability of the rankings in practical decision-making contexts. Additionally, incorporating rankings based on WRE would provide a more comprehensive assessment of the environmental sustainability of energy generation scenarios, enabling more informed and sustainable energy planning strategies.

Hypervolume Indicator

The graph depicting the Hypervolume Indicator, presented in Figure 6, provides insights into the convergence and diversity of solutions obtained through multi-objective optimization. The y-axis of the graph ranges from 0 to 0.40, representing the hypervolume indicator value, which is a measure of the volume of the objective space covered by a set of solutions. A higher hypervolume indicator value indicates a greater spread and coverage of the Pareto front, reflecting better convergence and diversity of solutions. Meanwhile, the x-axis denotes the performance metric, with a fixed value of 0.40. The hypervolume indicator is a widely used performance metric in multi-objective optimization to assess the quality of Pareto optimal solutions. It quantifies the extent to which the set of non-dominated solutions covers the objective space, providing insights into the convergence and spread of solutions along the Pareto front. A higher hypervolume indicator value indicates a more diverse and well-distributed set of solutions, representing a better trade-off between conflicting objectives.

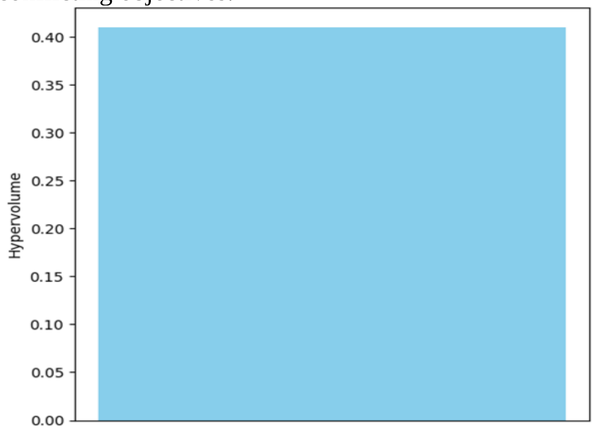

FIGURE 6. Hypervolume Indicator

The results depicted in the graph illustrate the hypervolume indicator value of 0.40, representing the convergence and diversity of solutions obtained through multi-objective optimization. The specific value of 0.40 indicates the extent to which the set of non-dominated solutions covers the objective space defined by the performance metric. A higher hypervolume indicator value suggests a more comprehensive exploration of the objective space and a greater diversity of solutions along the Pareto front. Understanding the hypervolume indicator is crucial for assessing the effectiveness and efficiency of multi-objective optimization algorithms in finding Pareto optimal solutions. By quantifying the convergence and diversity of solutions, the hypervolume indicator provides valuable insights into the performance of optimization algorithms and the quality of solutions obtained. It enables researchers and practitioners to evaluate the trade-offs between conflicting objectives and identify the most suitable solutions for decision-making. In this study, the hypervolume indicator value of 0.40 was derived from hypothetical data for demonstration purposes. While the specific hypervolume indicator value may vary depending on the problem characteristics and optimization algorithms used, the general trends observed in the graph provide valuable insights into the convergence and diversity of solutions obtained through multi-objective optimization. Future research could involve the application of multi-objective optimization algorithms to real-world problems and the analysis of actual hypervolume indicator values to validate the findings and assess the applicability of the metric in practical decision-making contexts. Additionally, comparative analyses and sensitivity studies could further enhance our understanding of the factors influencing the hypervolume indicator and its implications for multi-objective optimization.

Conclusion

1. The hybrid AI approach applied in this study demonstrates its efficacy in multi-objective optimization for environmental decision-making, offering a systematic framework for addressing complex challenges.
2. Through data collection, modeling, simulation, performance evaluation, and comparative analysis, the methodology provides comprehensive insights into the application of AI in optimizing environmental systems.
3. The results highlight the importance of understanding hourly variations of insolation and wind speed, essential for renewable energy applications and climate studies.
4. Rankings based on Levelized Energy Cost (LEC), unmet fraction, fuel consumption, and water resource efficiency (WRE) offer valuable insights into the cost-effectiveness, reliability, and sustainability of energy generation scenarios.
5. The Hypervolume Indicator analysis underscores the effectiveness of the multi-objective optimization approach in achieving diverse and well-distributed solutions along the Pareto front, enabling informed decision-making.

Data Availability Statement

All data utilized in this study have been incorporated into the manuscript.

Authors' Note

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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Embargo period: The article has no embargo period.

To cite this Article: N Penchalaiah and Ashok Koujalagi, Multi-Objective Optimization In Environmental Decision-Making: A Hybrid AI Approach, Information Technology and Management 1. 1 (2024): 1 - 7.