

Artificial Intelligence and Computational Optimization in Solar Energy Systems: A Survey of Single and Multi-Objective Methods

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Abstract - To increase the sustainability, affordability, and efficiency of renewable energy sources, solar energy systems must be optimized. As solar energy continues to gain prominence in international energy regulations, the need for sophisticated optimization approaches has become evident. This paper provides a comprehensive evaluation of single-objective and multi-objective optimization techniques utilized in solar energy systems. This evaluation aims to shed light on the critical role optimization plays in achieving optimal system performance and operational effectiveness by carefully analyzing the approaches, advantages, and challenges of each technique. In order to demonstrate how optimization strategies operate for a variety of solar technologies, including hybrid solar systems, photovoltaic (PV) systems, and solar thermal systems, the study compiles recent research and case studies. In contrast to single-objective optimization methods, which focus on optimizing a single criterion, such as energy output or cost, the study also looks at the drawbacks and trade-offs of multi-objective optimization techniques, which consider multiple, often incompatible goals at once, such as maximizing energy output while minimizing cost and environmental impact.

The survey explores the evolving subject of solar energy system optimization in further detail, including recent advancements such as the use of artificial intelligence (AI), machine learning, and digital twin technologies. These advancements have the potential to significantly improve the adaptability and efficiency of optimization processes in real-time applications. The paper ends by listing a number of important challenges, including the requirement for more comprehensive models that take into account computational complexity in addition to social, environmental, and economic factors.

The findings of the review are meant to act as a guide for future research and development in the area of solar energy optimization, establishing the framework for the development of more cost-effective, efficient, and sustainable solar energy systems. **Keywords:** artificial intelligence, photovoltaic systems, solar energy, optimization methods, single-objective optimization, and multi-objective optimization.

Keywords - Solar energy, Optimization techniques, Single-objective optimization, Multi-objective optimization, Photovoltaic systems, Artificial intelligence.

1. Introduction

Concerns over climate change and the depletion of fossil fuels have led to the rise of solar energy as a major contributor to global energy solutions. The implementation of solar technology must be optimized to satisfy a number of operational, environmental, and financial requirements. For solar energy systems to operate better, cost less, and produce more energy, optimization is crucial. Researchers use a variety of optimization techniques to accomplish these aims, with a primary emphasis on single-objective optimization and multi-objective optimization (MOO) frameworks. Optimizing one particular criterion, such as maximizing energy output or reducing costs, is the emphasis of single-objective optimization. This method works well when trade-offs are simpler and one aspect predominates in the decision-making process. Multi-objective optimization, on the other hand, takes into account several, frequently incompatible goals at once. For example, it seeks to reduce expenses while increasing energy efficiency and lessening the impact on the environment [1].

Multi-objective optimization (MOO) is a favored method for more complicated systems, such as hybrid solar energy systems that integrate many energy sources, because it is especially useful in situations where diverse performance indicators need to be balanced [7] [8].

For solar energy systems to be designed and implemented as efficiently as possible, it is essential to comprehend the advantages and disadvantages of both optimization approaches. These two optimization algorithms are examined in this paper along with a comparison of their approaches, case studies, and uses. Additionally, the use of digital twin technologies, machine learning, and artificial intelligence (AI) is investigated as a way to improve optimization procedures in real-time applications. By tackling some of the major optimization issues, such as computational complexity and the integration of economic, environmental, and social considerations, these cutting-edge technologies have the potential to

significantly increase the adaptability, efficiency, and scalability of solar energy systems [7] [8].

2. Methodology of Literature Selection

This review follows a systematic approach in selecting and analyzing relevant studies. Literature was identified from reputable databases including IEEE Xplore, ScienceDirect, and Scopus, using keywords such as "solar energy optimization," "single-objective optimization," and "multi-objective optimization." Selection criteria included publication date (last 10 years), peer-reviewed status, and relevance to PV, thermal, or hybrid solar systems. Duplicates and non-English papers were excluded to ensure quality and focus [20] [21].

2.1 Theoretical Background

Optimization in solar energy systems is grounded in operations research, thermodynamics, and systems engineering. Theoretical frameworks such as Pareto efficiency and convex optimization are crucial for understanding the behavior of multi-objective trade-offs. Additionally, concepts like energy conversion efficiency and life-cycle cost analysis are commonly employed to evaluate performance [22] [23]. Table 1 shows the computational time in our proposed procedure for the SHA1 hash function

Table 1 shows the summarizes key studies related to solar energy optimization, highlighting their research focus, methodologies, outcomes, challenges, and future recommendation.

Table 1. Shows a Summary of Key Studies on Solar Energy Optimization

Study	Research Focus	Methodologies Used	Improved Indicators	Challenges Encountered	Future Recommendations
Niu et al. (2019) [4]	Cost Minimization in Concentrated Solar Power (CSP) Systems	Linear Programming	Reduced operational costs, optimized material and land use	High computational demand for large-scale systems	Future research could focus on integrating more dynamic forecasting models to improve cost prediction.
Vargas et al. (2017) [3]	Optimizing Photovoltaic Systems in Urban Environments	Single-objective optimization	Increased energy generation, minimized land use	Lack of consideration for environmental factors in optimization	Future work could integrate environmental impact assessments alongside energy generation.
Ming et al. (2023) [6]	Multi-Objective Optimization in Hybrid Renewable Systems (Solar, Wind, and Batteries)	Genetic Algorithms, Particle Swarm Optimization	System efficiency, cost reduction, environmental impact	Complexity of dealing with multiple conflicting objectives	Further integration of real-time weather data and forecasting could enhance optimization accuracy.
Cao et al. (2024) [5]	Optimizing Solar Thermal Systems Using Genetic Algorithms	Genetic Algorithms	System efficiency, sustainability	Difficulty in scaling up solutions for large-scale implementations	Future studies could explore hybrid algorithms to improve scalability and adaptability.
Gupta et al. (2020) [7]	AI in Solar Energy Systems	Machine Learning, AI-based optimization	Energy production prediction, operational cost reduction	Data quality issues in real-time analysis	More emphasis on AI-based forecasting techniques could improve future solar energy systems.
Garcia et al. (2020) [8]	Integration of Solar Energy with Smart Grids	Smart Grid Integration	Power outage reduction, optimized energy distribution	Integration complexity with existing grid infrastructure	More advanced grid integration techniques could improve overall grid resilience and efficiency.
Kumar & Singh (2021) [20]	Review of Optimization Techniques in Solar Energy Systems	Systematic Review	Summary of techniques, identification of research gaps	Lack of unified frameworks for complex systems	Development of integrated hybrid optimization frameworks recommended.
Smith & Lee (2020) [21]	Selection Criteria in Energy	Methodology Analysis	Improved survey	Variability in survey scopes	Adoption of standardized selection

	Optimization Surveys		reliability and reproducibility		and evaluation criteria suggested.
Boyd & Vandenberghe (2004) [22]	Convex Optimization Theory and Applications	Theoretical Framework	Enhanced algorithmic efficiency and solution accuracy	Challenges in applying convex models to non-convex real-world problems	Future work to extend convex methods to approximate non-convex problems.
Bejan (2016) [23]	Advanced Engineering Thermodynamics	Thermodynamic Analysis	Improved system efficiency and sustainability	Complex thermodynamic modeling requirements	Encouraged integration of thermodynamic optimization with AI techniques.
Wang & Shahidehpour (2017) [24]	Optimization Techniques for Renewable Energy Systems	Literature Review	Identification of key methodologies and performance metrics	Balancing multi-objective criteria	Suggested more real-time and adaptive optimization methods.

3 Single-Objective Optimization

3.1. Definition and Methodologies

Single-objective optimization focuses narrowly on improving one specific performance metric. This approach is valuable for straightforward decision-making problems where one attribute dominates the performance outcomes. Common methodologies include:

- **Linear Programming (LP):** This technique is frequently used to minimize energy system costs, particularly when there are linear connections between variables.
- **Non-linear Programming (NLP):** Applied in situations where there are non-linear interactions between variables and limitations, such as in PV system performance modeling and energy generation processes.
- **Dynamic Programming (DP):** Benefits applications involving time-dependent decision-making, such as energy production scheduling and battery charge/discharge control.

The benefits of single-objective optimization in the solar sector have been shown by recent studies. In order to improve solar thermal power plants, for example, a study by [6] used an enhanced bare-bones multi-objective particle swarm optimization algorithm—applied in a single-objective context—which successfully decreased operating costs while increasing energy output [2]. These techniques are effective when the optimization problem is clearly stated and the trade-offs are small, but they might not be able to handle the intricacy and interdependency of several competing goals that are frequently present in contemporary energy systems.

3.2. Case Studies

3.2.1. Solar Photovoltaic (PV) Systems:

The practical utility of such techniques in geographically limited situations was highlighted by

their results, which demonstrated a significant increase in energy generation while minimizing land use [3].

3.2.2. Concentrated Solar Power (CSP):

Zha et al. applied single-objective optimization to CSP systems to minimize land and material costs. The approach led to substantial reductions in total cost without sacrificing energy output performance, showcasing how targeted optimization can effectively support cost-efficiency goals in large-scale solar [6].

3.3. Limitations

There are many disadvantages to single-objective optimization despite its simple methodology:

- **Ignores Trade-offs:** By focusing solely on one criterion, single-objective optimization can lead to suboptimal configurations when trade-offs are essential.
- **Over-Simplification:** Complex solar systems often require the consideration of multiple factors such as monetary, environmental, and technical constraints, which single-objective methods cannot adequately address [5].

4. Multi-Objective Optimization (MOO)

4.1. Definition and Methodologies

Multi-objective optimization contrasts with its single-objective counterpart by simultaneously addressing multiple, often conflicting, goals. MOO typically involves finding a Pareto front, where no single objective can be improved without degrading another. Some prevalent methodologies include:

- **Genetic Algorithms (GA):** Use a population-based search mechanism to explore potential solutions, particularly suitable for complex landscape problems in solar configurations.
- **Particle Swarm Optimization (PSO):** Mimics social behavior patterns to converge towards optimal solutions, effective in collaborative optimization efforts.

- **Evolutionary Strategies (ES):** Focus on self-adaptation mechanisms to handle the performance landscape dynamically.

Significant research has illustrated the effectiveness of MOO in improving solar energy systems. As reported by Launay et al., genetic algorithms can be adeptly applied to optimize solar thermal energy systems, providing valuable insight into trade-offs among economic, social, and environmental factors [6].

4.2. Case Studies

- **Hybrid Energy Systems:** Ming et al. explored MOO in hybrid renewable systems integrating solar, wind, and battery systems to balance cost, reliability, and environmental implications,

yielding a Pareto-efficient set of configurations [7].

- **Microgrid Efficiency:** Zhou et al. applied MOO to enhance the operational efficiency of microgrids powered by renewables. Their findings emphasized the benefits of MOO in determining optimal dispatch strategies that cater to multiple objectives such as minimizing costs while maintaining voltage stability [8].

Table 2 shows the summarizes key recent studies on optimization techniques in solar energy systems, highlighting their research focus, main findings, and contributions to improving system efficiency and performance.

Table 2. Shows The Summarizes Key Recent Studies

Study	Research Focus	Key Findings
Niu et al. (2019) [4]	Cost Minimization in Concentrated Solar Power (CSP) Systems	<ul style="list-style-type: none"> • Application of linear programming for cost optimization in material and land use. • Significant operational cost reductions while balancing investment costs with energy yield.
Vargas et al. (2017) [3]	Optimizing Photovoltaic Systems in Urban Environments	<ul style="list-style-type: none"> • 25% increase in energy generation through optimized panel layout and angle. • Minimized land use while maximizing energy output.
Ming et al. (2023) [6]	Multi-Objective Optimization in Hybrid Renewable Systems (Solar, Wind, and Batteries)	<ul style="list-style-type: none"> • 18% improvement in system efficiency compared to traditional systems. • Cost reduction and better balance of cost, efficiency, and environmental impact.
Cao et al. (2024) [5]	Optimizing Solar Thermal Systems Using Genetic Algorithms	<ul style="list-style-type: none"> • Achieved an ideal balance between economic and environmental sustainability. • Improved system efficiency by optimizing energy storage and reducing energy loss.
Gupta et al. (2020) [7]	Use of AI in Solar Energy Systems	<ul style="list-style-type: none"> • Machine learning improved energy production prediction accuracy by 92%. • Real-time data analysis using AI enhanced energy management and reduced operational costs.
Garcia et al. (2020) [8]	Integration of Solar Energy with Smart Grids	<ul style="list-style-type: none"> • 30% reduction in power outages due to integration of solar energy with smart grids. • Improved energy distribution based on real-time demand.
Kumar & Singh (2021) [20]	Review of Optimization Techniques in Solar Energy Systems	<ul style="list-style-type: none"> • Comprehensive analysis of classical and AI-based optimization methods. • Identified genetic algorithms and particle swarm optimization as most effective for multi-objective problems.
Smith & Lee (2020) [21]	Selection Criteria and Methodologies in Energy Optimization	<ul style="list-style-type: none"> • Emphasized rigorous criteria for study selection in optimization surveys. • Highlighted the importance of combining quantitative and qualitative methodologies for comprehensive reviews.
Boyd & Vandenberghe (2004) [22]	Convex Optimization Theory	<ul style="list-style-type: none"> • Provided foundational principles and mathematical formulations for convex optimization. • Widely used as a theoretical base for

		optimization in energy systems.
Bejan (2016) [23]	Advanced Engineering Thermodynamics	<ul style="list-style-type: none"> Detailed principles of thermodynamics critical for efficient solar thermal system design. Emphasized entropy generation minimization to improve system efficiency.
Wang & Shahidehpour (2017) [24]	Optimization Techniques for Renewable Energy Systems	<ul style="list-style-type: none"> Reviewed classical and heuristic methods for renewable energy optimization. Recommended hybrid techniques combining deterministic and metaheuristic methods for improved results.

5. Challenges

While MOO presents significant advantages, challenges include:

- **Computational Demand:** It can be computationally intense, especially in high-dimensional objective spaces.
- **Complexity of Solutions:** To choose the best trade-off solutions from the Pareto front, the findings frequently require professional interpretation, which complicates the decision-making process [9] [10] [11].
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Key Observations from the Results:

- Different programming techniques, such as linear and dynamic programming, have proven effective in cost reduction and efficiency improvement in solar energy systems.
- Multi-objective optimization (MOO) played a significant role in improving cost and efficiency in hybrid solar energy systems.
- Artificial intelligence significantly increased the accuracy of energy predictions and enhanced real-time system performance.
- Hybrid systems demonstrated improvements in both cost-efficiency and system performance, highlighting the importance of integrating different energy sources.

6. Challenges and Future Directions

Both single-objective and MOO methods have advanced, but there are still a number of issues. The intrinsic unpredictability and erratic nature of solar energy as a result of meteorological and seasonal variations is one of the main problems. It is challenging to maintain constant performance because of these variations, which have a direct impact on the stability and predictability of energy generation. Strong optimization models that can manage uncertainty and instantly adjust to changing situations are therefore becoming more and more necessary. In order to improve operational scheduling and planning in renewable energy systems, Alhmoud and Nusair emphasized how

including precise forecasting and uncertainty modeling might lessen these effects [12].

In order to provide a more flexible optimization paradigm that captures important trade-offs and permits targeted decision-making, future research could investigate hybrid optimization frameworks that integrate single and multi-objective techniques. Investing in more understandable approaches and resources for deciphering intricate MOO solutions will also improve these strategies' practicality [13] [14].

References

- [1] Fettah, B., & Pasaoglu, G. (2024). Optimization techniques for renewable energy systems: A comprehensive review. *Renewable and Sustainable Energy Reviews*, 140, 110715.
- [2] Hossain, M. S., & Ali, M. (2021). Optimization Techniques for Solar Power Systems: A Review of Current Trends. *Renewable Energy Reviews*, 134, 256–274.
- [3] Launay, C., & Gosselin, F. (2019). Optimization of solar thermal power systems using improved particle swarm optimization. *Energy Procedia*, 157, 568–575.
- [4] Vargas, R., & Alvarez, D. (2017). Optimization of photovoltaic systems in urban environments. *Solar Energy*, 151, 50-60.
- [5] Zhao, H., & Liu, Y. (2020). A Review of Multi-Objective Optimization Methods in Solar Power System Design. *Journal of Solar Energy Engineering*, 142(5), 051006.
- [6] Niu, Z., & Zhao, Z. (2019). Cost minimization strategies for concentrated solar power systems. *Renewable Energy*, 132, 987-998.
- [7] Mohammadi, K., & Shayanfar, H. A. (2022). Hybrid Approaches to Optimization in Solar Energy Systems. *Renewable and Sustainable Energy Reviews*, 153, 111772.
- [8] Cao, X., et al. (2024). Genetic algorithms for optimizing solar thermal energy systems. *Energy Reports*, 10, 140–150.
- [9] Ming, L., & Xie, X. (2023). Multi-objective optimization for hybrid renewable energy systems. *Energy Reports*, 9, 210-220.
- [10] Vaish, P., & Patel, P. (2023). Multi-objective optimization for operational planning in renewable-powered microgrids. *Energy*, 263, 124739.

- [11] Ferreira, F., & Silva, P. (2020). Integrating forecasting in renewable energy systems for improved optimization. *Renewable Energy*, 143, 234-246.
- [12] Khan, M. J., & Iqbal, M. T. (2020). Computational Methods in Solar Energy System Optimization. *Solar Energy*, 202, 150–168.
- [13] Chakraborty, P., & Saha, S. K. (2021). Multi-Objective Optimization in Solar Thermal Systems: Techniques and Applications. *Energy Conversion and Management*, 227, 113591.
- [14] Mollah, M. B., & Tushar, S. (2021). Optimization of Solar Photovoltaic and Hybrid Systems using Genetic Algorithms and Particle Swarm Optimization. *Renewable Energy*, 163, 159–175.
- [15] Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2), 182–197.
- [16] Talbi, E.-G. (2009). *Metaheuristics: From design to implementation*. John Wiley & Sons.
- [17] Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization*, 26(6), 369–395.
- [18] Zhang, X., & Wang, L. (2022). Recent advances and research gaps in the optimization of solar photovoltaic systems. *Renewable and Sustainable Energy Reviews*, 153, 111773.
- [19] Hassan, M. A., & Elhassan, E. A. (2023). Challenges and future directions in the integration of AI-based optimization for renewable energy systems. *Energy Reports*, 9, 1450–1465.
- [20] Kumar, A., & Singh, R. (2021). A systematic review on optimization techniques in solar energy systems. *Renewable Energy Reviews*, 150, 111458.
- [21] Smith, J., & Lee, H. (2020). Selection criteria and methodologies in energy optimization literature surveys. *Journal of Cleaner Production*, 270, 122414.
- [22] Boyd, S., & Vandenberghe, L. (2004). *Convex Optimization*. Cambridge University Press.
- [23] Bejan, A. (2016). *Advanced Engineering Thermodynamics*
- [24] Wang, J., & Shahidehpour, M. (2017). Optimization Techniques for Renewable Energy Systems: A Review. *Renewable and Sustainable Energy Reviews*, 77, 211-224.
<https://doi.org/10.1016/j.rser.2017.03.045>