

Optimization of renewable energy systems using operations research techniques

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Abstract

The global transition to renewable energy demands advanced analytical and decision-support tools capable of addressing the complex challenges inherent in the design, planning, and operation of renewable energy systems. Spanning the decade from 2015 to 2025, this study places particular emphasis on the application of operations research methodologies aimed at enhancing the performance and efficiency of such systems. A diverse range of mathematical programming techniques including linear programming, nonlinear programming, hybrid optimization, and multi-objective optimization, among others have been applied to varying degrees across numerous domains to tackle renewable energy challenges. The paper examines the roles played by microgrid management, grid integration, energy storage planning, power generation scheduling, and demand-side management within the broader context of energy system optimization. Through an analysis of prevailing trends and notable technological advancements, the study systematically classifies optimization problems based on their evolution, solution methodologies, and areas of application. Critical research gaps identified within this fast-growing field particularly concerning uncertainty modelling, computational efficiency, and real-world applicability are highlighted, thereby charting important directions for future investigation. This work is intended to serve as a valuable reference for both researchers and industry practitioners who leverage operations research tools to advance and optimize renewable energy systems.

Keywords: Operation research, Renewable energy, Linear programming.

1. Introduction and Background

Over the past ten years, the shift from energy systems that rely on fossil fuels to those that use renewable energy sources has picked up a lot of speed. People are worried about climate change, energy security, and the fact that renewable technology is getting cheaper, which is causing this trend. But the fact that renewable resources are inherently variable and uncertain, as well as the fact that they are spread out, makes it very hard to plan and run an energy system (Liang and Qiu, 2020).

Energy systems optimization is the process of creating, planning, and executing systems that make, change, store, and move energy to reach particular objectives, including cutting costs, making systems more reliable, or cutting down on emissions. As more and more renewable energy sources are employed, it is harder and harder to optimize because:

1. Sources of renewable energy that aren't constantly there and vary over time
2. Renewable resources are found in many areas.
3. Need for technology that can be utilized in numerous ways and kept
4. Difficult market arrangements and regulations
5. Many aims that frequently conflict with one another in the social, economic, and environmental spheres

Using mathematical models, optimization tools, and decision-analytic techniques, operations research (OR) helps to systematically address these problems. For individuals that have to design and run increasingly sophisticated renewable energy systems, these techniques have been really useful (Prakash and Khatod, 2019).

With an emphasis on developments from 2015 to 2025, this study seeks to collect the most recent data on the application of operations research approaches for the optimization of renewable energy systems. Our objective is to offer researchers and practitioners a structured comprehension of the field and to identify promising directions for future research by organizing the literature according to problem types, solution methodologies, and application domains.

2. Operations Research Techniques in Renewable Energy Systems

Operations research incorporates a wide variety of mathematical and analytical methods that are designed to enhance the quality of decision-making. The mathematical formulation and solution approaches of these techniques can be used to classify them into various categories within the context of renewable energy systems.

2.1 Mathematical Programming Techniques

Numerous energy system optimization issues are fundamentally rooted in mathematical programming. The primary mathematical programming techniques utilized in renewable energy optimization are summarized in Table 1.

Table 1. Mathematical Programming Techniques in Renewable Energy Optimization

Technique	Key Characteristics	Major Applications	Key References
Linear Programming (LP)	Linear objective and constraints; continuous variables	Economic dispatch; simple resource allocation	Soares et al. (2020); Ma et al. (2017)
Mixed Integer Linear Programming (MILP)	LP with some integer variables	Unit commitment; capacity expansion planning; microgrid design	Li et al. (2020); Jin et al. (2018); Li et al. (2021)
Non-linear Programming (NLP)	Non-linear objective and/or constraints	Power flow optimization; energy storage operation	Li et al. (2019); Saez-de-Ibarra et al. (2016)
Mixed Integer Non-linear Programming (MINLP)	NLP with some integer variables	Combined heat and power optimization; complex system design	Elsido et al. (2019); Moretti et al. (2021)
Dynamic Programming (DP)	Sequential decision problems	Energy storage management; multi-stage planning	Li et al. (2022); Huang et al. (2022)

Technique	Key Characteristics	Major Applications	Key References
Multi-objective Optimization	Multiple, often conflicting objectives	Sustainability assessment; trade-off analysis	Perera et al. (2017); Mavromatidis et al. (2018)
Stochastic Programming	Explicitly incorporates uncertainty	Planning under uncertain renewable generation	Lara et al. (2018); Tan et al. (2018)
Robust Optimization	Worst-case optimization under uncertainty	Grid resilience; reliable system design	Moret et al. (2020); Soroudi and Keane (2015)

Linear Programming is a way of using math to solve problems. It works with equations and rules. To find the solution to Linear Programming problems we can use methods that have been around, for a while because they work well with computers. Linear Programming is often used in systems that use energy to figure out how to use resources in the best way and solve problems with getting energy to where it is needed. Linear Programming helps with this by making sure everything runs smoothly and resources are used wisely (Soares et al., 2020).

Mixed Integer Linear Programming is a method that comes from programming. It is really useful when we have to choose between things like unit commitment or capacity planning or technology selection. We use Mixed Integer Linear Programming to make these choices because it can handle tasks like unit commitment and capacity planning and technology selection. It does this by using kinds of variables that are either zero or one or integers. Mixed Integer Linear Programming has been used a lot to help design and run microgrids especially when we have to pick which units to use and there are a lot of options. Mixed Integer Linear Programming is good, at this because it can deal with the fact that the options all very different (Li et al., 2020).

Natural Language Processing is used when we have a problem that does not work in a line. This happens with things like batteries running out of power or getting power from one place to another or using resources to make energy. These Natural Language Processing problems are really hard to solve with special tools to help us. They are even harder, than problems that do work in a line (Li et al., 2019).

Combining the complexity of integer variables with non-linear functions, Mixed Integer Non-linear Programming (MINLP) is among the most challenging but versatile frameworks. MINLP (Elsido et al., 2019) combines heat and power system optimization with complicated renewable energy system design challenges when both discrete judgments and non-linear physics have to be considered simultaneously.

2.2 Heuristic and Metaheuristic Approaches

For difficult, large-scale challenges challenging to solve with standard mathematical programming methods, heuristic and metaheuristic solutions offer reasonable replacements. Table 2 emphasizes the primary metaheuristic and heuristic techniques applied in renewable energy optimization.

Table 2. Heuristic and Metaheuristic Approaches in Renewable Energy Optimization

Technique	Key Characteristics	Major Applications	Key References
Genetic Algorithms (GA)	Evolutionary approach inspired by natural selection	Complex system design; parameter tuning	Sharma et al. (2017); Khan and Javaid (2020)
Particle Swarm Optimization (PSO)	Swarm intelligence algorithm	Distributed energy resource scheduling; solar PV optimization	Liao et al. (2018); Veni et al. (2019)
Simulated Annealing (SA)	Probabilistic technique for approximating global optimum	Wind farm layout optimization; complex system design	Rahman et al. (2021)
Tabu Search (TS)	Local search with "memory" to avoid revisiting solutions	Unit commitment with renewables; energy storage scheduling	Katsigiannis and Georgilakis (2012)
Ant Colony Optimization (ACO)	Swarm intelligence inspired by ant behavior	Renewable energy system configuration; energy routing	Veni et al. (2019)
Differential Evolution (DE)	Population-based optimization	Parameter estimation; complex system design	Sharma et al. (2017)
Artificial Neural Networks (ANN)	Machine learning approach	Renewable energy forecasting; hybrid optimization approaches	Vazquez-Canteli et al. (2019)
Hybrid Metaheuristics	Combination of multiple techniques	Complex large-scale problems; multi-objective optimization	Khan and Javaid (2020)

Genetic Algorithms are really good at helping us figure out how to make renewable energy better. They are very useful when we have to deal with problems that have a lot of possible solutions. Renewable energy optimization is an area where Genetic Algorithms are used a lot. Genetic Algorithms are good at handling problems that're not straightforward and have many different parts to consider. They have been very successful, in finding the way to set up hybrid renewable energy systems, in these systems we want to find the way to combine different ways of making energy and storing it so that we get the most energy out of our systems. Genetic Algorithms help us do that by trying out different combinations and finding the one that works best (Sharma et al., 2017).

Particle Swarm Optimization or PSO for short is really good at helping us figure out the settings for solar panels and scheduling energy resources that are spread out in different places. It gets its ideas from the way birds fly together in groups and fish swim in schools. People are using Particle Swarm Optimization more and more because it is easy to understand it works fast. It is very good at solving complicated problems that are not straightforward like nonlinear optimization problems, with Particle Swarm Optimization (Liao et al., 2018).

Recently people have been paying attention to hybrid metaheuristic approaches. These hybrid metaheuristic approaches combine two or more optimization methods. They do this to make the optimization methods work better together. Hybrid metaheuristic approaches use the things about each optimization method to help the other optimization methods. This way hybrid metaheuristic approaches can make up for the weaknesses of each optimization method on its

own. So hybrid metaheuristic approaches can give us results when we use them to optimize things. We get robust and effective optimization performance, from hybrid metaheuristic approaches (Yu et al., 2025).

2.3 Simulation-Based Optimization

Renewable energy systems have a lot of issues that need to be solved. To solve these problems, we use something called simulation-based optimization. This method combines good simulation models with optimization techniques. The simulation models are very accurate. The optimization techniques help us find the best solution. We use simulation-based optimization to deal with the issues, in renewable energy systems. Simulation-based optimization is a way to make renewable energy systems better. Table 3 shows the most important optimization methods that use simulation.

Table 3. Simulation-Based Optimization Approaches in Renewable Energy Systems

Technique	Key Characteristics	Major Applications	Key References
Monte Carlo Simulation	Statistical sampling for uncertainty analysis	Risk assessment; probabilistic planning	Koltsaklis et al. (2019)
Agent-Based Modeling	Bottom-up simulation of autonomous agents	Energy market simulation; consumer behavior	Klein et al. (2019); Ringler et al. (2022)
System Dynamics	Feedback-based simulation of complex systems	Long-term energy transition planning	Aslani et al. (2018); Eker et al. (2020)
Discrete Event Simulation	Process-focused simulation of sequential events	Operational logistics; maintenance scheduling	Sánchez-Úbeda et al. (2017)
Surrogate Model-Based Optimization	Uses approximation models to reduce computational burden	Complex system design; sensitivity analysis	Tian et al. (2020)
Simulation-Optimization Integration	Direct coupling of simulation with optimization algorithms	Complex hybrid renewable energy systems	Khan and Javaid (2020)

Monte Carlo simulation is very useful for dealing with uncertainty in renewable energy systems, such as changes in solar or wind resources. This method uses random samples from probability distributions to provide a probabilistic evaluation of risk analysis and system performance (Koltsaklis et al., 2019).

Energy markets with many stakeholders and consumer behavior are well suited for agent-based modeling since it mimics the interactions and actions of independent agents. Using this method, researchers have looked at how peer-to-peer energy trading changes over time and how letting people make decisions in different places affects the results for the whole system (Klein et al., 2019).

Surrogate model-based optimization lowers processing load by means of simpler mathematical representations of sophisticated simulation models. For issues needing many function evaluations, such sensitivity analysis and robust design optimization of renewable energy systems, this method is especially helpful (Tian et al., 2020).

3. Application Domains in Renewable Energy Systems

Within renewable energy systems, operations research methods have been used in many different fields. Review of the most important application fields in this section exposes the particular issues and solutions used in every sphere.

3.1 Energy Generation Planning and Capacity Expansion

Planning for energy production means finding the best combination and capacity of several energy sources across a planning horizon. Important uses and techniques in this field are compiled in Table 4.

Table 4. Operations Research in Energy Generation Planning and Capacity Expansion

Application Area	Key Challenges	OR Techniques Applied	Key References
National/Regional Energy Planning	Long time horizons; policy constraints; uncertainty	MILP; Stochastic Programming; System Dynamics	Lopion et al. (2018); Ringkjøb et al. (2019); Pickering et al. (2022)
Renewable Portfolio Optimization	Resource complementarity; reliability constraints	Multi-objective Optimization; Robust Optimization	Perera et al. (2017); Sawle et al. (2018)
Spatial Planning for Renewables	Geographic constraints; transmission considerations	GIS-integrated Optimization; Location-Allocation Models	Höfer et al. (2016); Jia et al. (2023)
Generation Expansion Planning	Investment timing; technological learning	Dynamic Programming; Real Options Analysis	Bistline (2018); Guerra et al. (2020)
Decommissioning and Transition Planning	Legacy system constraints; just transition considerations	Multi-stage Optimization; Multi-criteria Decision Analysis	Olauson et al. (2022)

National and regional energy plans often use MILP or stochastic programming methods to find the best way to expand capacity over a period of decades. Modern models have included ever more precise depictions of grid integration issues and renewable variability (Ringkjøb et al., 2019).

Renewable portfolio optimization seeks to find the best combination of renewable technologies to meet particular goals including cost lowering, reliability maximization, or emissions reduction. Commonly used to examine trade-offs between these conflicting objectives are multi-objective optimization approaches (Perera et al., 2017).

As the spatial distribution of renewable resources greatly influences system performance, spatial planning for renewables has become rather important. Including spatial limits and transmission infrastructure, Geographic Information System (GIS) combined optimization models assist to find best sites for renewable energy plants (Höfer et al., 2016).

3.2 Grid Integration and Power System Operation

Combining different kinds of renewable energy into current power systems creates special operational difficulties that operational research tools can help to solve. Important uses in this field are listed in Table 5.

Table 5. Operations Research in Grid Integration and Power System Operation

Application Area	Key Challenges	OR Techniques Applied	Key References
Unit Commitment with Renewables	Variability; uncertainty; system flexibility	Stochastic MILP; Robust Optimization	Koltsaklis and Dagoumas (2018); Dehghan et al. (2018)
Transmission Expansion Planning	Network constraints; renewable integration	MILP; Game Theory; Decomposition Methods	Lumbreras and Ramos (2017); Jia et al. (2023)
Ancillary Services Provision	Fast response requirements; market design	MILP; Stochastic Optimization	Jin et al. (2018); Soares et al. (2020); Peker et al. (2022)
Congestion Management	Network constraints; renewable curtailment	OPF; Market-based Approaches	Pillay et al. (2019)
Power Quality and Stability	Dynamic constraints; protection coordination	Non-linear Programming; Heuristic Approaches	Gonzalez-Longatt et al. (2021)

Unit commitment with renewables is finding the best way to schedule regular generators while also considering how much renewable resources can change and how unsure we are about them. Commonly employed to solve this issue are stochastic MILP models, which include demand and renewable generation scenarios (Koltsaklis and Dagoumas, 2018).

Planning for transmission expansion has changed to particularly handle the difficulties of integrating renewable energy, including the requirement to link load centers to distant renewable resources and control bigger power flows. For these big-scale challenges, MILP models with decomposition methods have been shown to be successful (Lumbreras and Ramos, 2017).

Increasing renewable penetration has made ancillary services provision more important since system operators require flexible resources to keep the grid stable. Considering the capacities of several resources including renewables, storage, and demand response, optimization models help to define the best procurement and distribution of these services (Soares et al., 2020).

3.3 Energy Storage Systems

Table 6 illustrates the key applications of operations research in improving energy storage. Energy storage systems are crucial for facilitating the use of renewable energy, as they provide flexibility and make it easier to manage changes in the amount of energy we can obtain from it.

Table 6. Operations Research in Energy Storage Systems

Application Area	Key Challenges	OR Techniques Applied	Key References
Storage Technology Selection	Technology characteristics; application requirements	Multi-criteria Decision Analysis; MILP	Balaman et al. (2021); Chen et al. (2023)
Storage Sizing and Siting	Location-specific benefits; network constraints	MILP; GIS-integrated Optimization	Harati et al. (2018); Alhamwi et al. (2017)
Storage Operation	Degradation; uncertainty; market	Stochastic Dynamic	Hashmi et al. (2019); Li et

Application Area	Key Challenges	OR Techniques Applied	Key References
Strategies	participation	Programming; MPC	al. (2022)
Value Stacking	Multiple revenue streams; regulatory constraints	MILP; Stochastic Optimization	Li et al. (2020); Akram et al. (2019)
Seasonal Storage Planning	Long-duration cycles; inter-seasonal balancing	MILP; System Dynamics	Sepulveda et al. (2021)

Mixed linear programming models and multi-criteria decision analysis help evaluate trade-offs between the following elements to determine the best storage technologies for specific uses, taking into account factors such as lifespan, cost, efficiency, and response time (Balaman et al., 2021).

To determine the optimal time for charging and unloading storage systems, storage management strategies address the complex issue of maximizing value. Predictive model control techniques and stochastic dynamic programming take into account changes in renewable energy production, demand, and market prices (Hashmi et al., 2019).

Value accretion optimization seeks to maximize the general worth of storage systems, including frequency control, power balancing, and renewable energy integration by offering several services concurrently. Linear hybrid programming models with appropriate boundaries can achieve the best possible multi-value streams while considering operational constraints (Li et al., 2020).

3.4 Microgrids and Distributed Energy Resources

Table 7 illustrates the most important applications of this field. The shift from centralized to decentralized energy systems, microgrids, and distributed energy resources represents a radical change that creates new opportunities and challenges in the field of optimization.

Table 7. Operations Research in Microgrids and Distributed Energy Resources

Application Area	Key Challenges	OR Techniques Applied	Key References
Microgrid Design and Sizing	System reliability; self-sufficiency; resilience	MILP; Multi-objective Optimization	Mandelli et al. (2016); Fathima and Palanisamy (2015)
Microgrid Operation	Balance between self-consumption and grid interaction	MPC; Real-time Optimization	Jin et al. (2017); Vergara et al. (2019)
Energy Management Systems	Multi-carrier integration; user preferences	Hierarchical Optimization; Distributed Algorithms	Khorramdel et al. (2018); Nguyen et al. (2023)
Peer-to-Peer Energy Trading	Market design; pricing mechanisms	Game Theory; Multi-agent Optimization	Morstyn et al. (2018); Tushar et al. (2018)
Resilience Enhancement	Critical load service during emergencies	Robust Optimization; Chance-constrained Programming	Hussain et al. (2019)

Planning and scaling a microgrid requires selecting the most suitable mix and quantity of distributed energy sources to achieve specific goals such as reducing costs, increasing reliability, or mitigating emissions. Multi-objective mixed linear programming models help to systematically evaluate these trade-offs (Mandelli et al., 2016).

Determining the optimal real time allocation of distributed resources, taking into account factors such as renewable energy production, load behavior, storage status, and network conditions, is the primary goal for improving the operational efficiency of microgrids. To address the dynamic nature of this issue, predictive model-based control methods become highly effective (Jin et al., 2017).

Improving energy exchange between individuals contributes to solving the problem of designing market mechanisms and trading tactics in distributed energy systems. Game theory helps us understand how people make decisions in markets. It shows us what market participants do and how they behave. We can use this information to find out what makes some markets work better than others. Game theory and looking at factors at the same time are good tools for this. They help us see what makes a market successful. We can use game theory to model what market participants do and find market structures. Market structures are the ways that markets are set up and organized. Game theory is very useful for this. It helps us make decisions, about markets and how they work (Morstyn et al., 2018).

3.5 Demand-Side Management and Energy Efficiency

Renewable energy systems really need demand-side management and energy efficiency. These things are important because they help with demand flexibility and they decrease the amount of energy that we use. The main ways that demand side management and energy efficiency are used in this area are shown in Table 8. Demand-side management and energy efficiency are crucial, for energy systems.

Table 8. Operations Research in Demand-Side Management and Energy Efficiency

Application Area	Key Challenges	OR Techniques Applied	Key References
Demand Response Program Design	Consumer behavior; market design	Game Theory; Mechanism Design	Ma et al. (2017); Maharjan et al. (2013)
Load Shifting and Scheduling	Consumer inconvenience; system constraints	MILP; MPC	Siano and Sarno (2017); Veni et al. (2019); Huang et al. (2022)
Energy Efficiency Investment	Portfolio optimization; uncertainty in savings	Stochastic Programming; Real Options Analysis	Gerarden et al. (2017); Peng et al. (2020); Kampelis et al. (2022)
Building Energy Management	Thermal dynamics; occupant comfort	MPC; Reinforcement Learning	Oldewurtel et al. (2012); Vazquez-Canteli et al. (2019)
Electric Vehicle Integration	Charging infrastructure; grid impacts	MILP; Stochastic Optimization	Chen et al. (2016); Clement-Nyns et al. (2010); Rahmani et al. (2023)

Designing a demand response program calls for creating incentives and market platforms to inspire consumers to participate in demand elasticity initiatives. Researching the intended interactions between customers and service providers and developing an effective reward system are made easier with game theory and mechanism design techniques (Maharjan et al., 2013).

Upgrading load shifting and regulating operation aims to find the most suitable timing for flexible loads to match renewable energy production or to reduce costs. Usually used to represent the objectives and limitations of load scheduling challenges are MILP and model predictive control techniques (Siano and Sarno, 2017).

Optimizing energy use in buildings takes into account the complicated interaction among the thermal qualities of a structure, the comfort requirements of its occupants, and the effectiveness of its energy systems. Approaches based on predictive modelling and emergence learning have demonstrated encouraging outcomes in modifying to match shifting usage patterns and surroundings (Vazquez-Canteli et al., 2019).

4. Emerging Trends and Future Research Directions

Policy changes, and technological advances are helping the renewable energy industry keep growing quickly. Table 9 lays out future study goals and developing trends.

Table 9. Emerging Trends and Future Research Directions in Renewable Energy Systems Optimization

Trend/Direction	Description	Key References
Integrated Energy Systems	Optimization across multiple energy carriers and sectors	Brown et al. (2018); Ridha et al. (2021)
Uncertainty and Risk Management	Advanced techniques for modeling and mitigating uncertainty	Stratigakos et al. (2022)
Distributed and Hierarchical Optimization	Scalable approaches for large-scale distributed systems	Molzahn et al. (2017); Baker et al. (2018)
Data-Driven and Learning-Based Approaches	Integration of machine learning with traditional optimization	Vazquez-Canteli et al. (2019); Chen et al. (2022)
Socio-Technical System Optimization	Incorporating social factors and human behavior	Jenkins et al. (2018); Köhler et al. (2019); Sovacool et al. (2021)
Circular Economy and Life Cycle Considerations	End-of-life management; resource recovery optimization	Cucchiella et al. (2015)

4.1 Integrated Energy Systems

Integrated energy systems' growth centers on how several energy resources electricity, heat, and gas interact with several industries including transportation, industry, and energy itself. Recent analyses have explored the creation of designs that embody these interactions and demonstrate the potential for integration across different renewable energy sectors (Brown et al., 2018).

Future studies in this area are likely to focus on:

- Creation of computer-friendly models for extensive integrated systems
- Consideration of sector-specific dynamics and operational limitations
- Combining long-term planning with short-term operational choices
- Mechanisms of coordination spanning hitherto independent energy sectors

4.2 Uncertainty and Risk Management

As renewable penetration grows, so does the relevance of good energy system uncertainty management. Important research subjects have become advanced methods of risk evaluation and uncertainty modeling (Stratigakos et al., 2022).

Future research directions include:

- Creation of reliable scalable stochastic optimization methods
- Modeling of sophisticated uncertainties and their relationships
- Combining long-term planning uncertainty with short-term operational uncertainty
- Risk-aware decision-making models strike several stakeholder points of view.

4.3 Distributed and Hierarchical Optimization

The growing decentralization of energy systems calls for the creation of distributed optimization methods able to respect privacy and computing limits while coordinating actions across several independent actors (Molzahn et al., 2017).

Key research directions in this area include:

- Scalable dispersed algorithms for very big systems
- privacy-preserving optimization strategies
- Mechanisms of coordination across layers of hierarchical decision
- Market designs that match system-level goals with dispersed decision-making

4.4 Data-Driven and Learning-Based Approaches

There are promising opportunities to address complex renewable energy challenges through the integration of machine learning with traditional optimization techniques (Vazquez-Canteli et al., 2019).

Future research in this area will likely focus on:

- Reinforcement learning for optimization and adaptive control
- Surrogate modeling to lower processing costs
- Use transfer learning to apply expertise across related systems.
- Readable machine learning models to help with decisions

5. Challenges and Limitations

There are still a number of obstacles and limits, even if renewable energy systems optimization has advanced noticeably. Table 10 offers a synopsis of these problems and possible solutions for them.

Table 10. Challenges and Limitations in Renewable Energy Systems Optimization

Challenge/Limitation	Description	Potential Approaches
Computational Complexity	Large-scale problems with high dimensionality	Decomposition methods; Parallel computing; Approximate algorithms
Model Accuracy vs. Tractability	Trade-off between detail and solvability	Multi-level modeling; Hybrid approaches; Adaptive refinement
Data Availability and Quality	Limited or unreliable data for model parameterization	Data fusion techniques; Uncertainty analysis; Robust formulations
Algorithm Selection and Parameter Tuning	Difficulty in choosing appropriate methods	Automated algorithm selection; Hyperparameter optimization
Implementation Gap	Disconnect between academic models and practical implementation	Stakeholder engagement; User-friendly tools; Decision support systems
Interdisciplinary Integration	Need for expertise across multiple domains	Collaborative frameworks; Knowledge translation; Integrated modeling platforms

Particularly for large-scale challenges spanning several time scales, high spatial resolution, and uncertainty awareness, computational complexity continues to be a major issue. Parallel processing, decomposition techniques, and approximate algorithms provide possible answers but usually need problem-specific modifications.

Modelers still have difficulty balancing model accuracy and manageability. Achievement of this alignment shows promise in multilevel modeling methods, which mix basic explanations of other features with fused models of fundamental components.

Many fields now find it difficult to close the implementation barrier between real-world use and theoretical research. We need to pay attention to getting stakeholders involved making tools that are simple to use and creating systems that help people make decisions. These systems should take the results of improvement efforts. Turn them into ideas that people can actually use. We have to make sure that stakeholders are a part of this process and that the tools we design are easy for them to use. Decision support systems are also important because they help stakeholders take the information they have and turn it into plans. This will help us close the gap and make progress with improvement outcomes and turn these outcomes into practical ideas that stakeholders can use.

6. Conclusion

This study provides an overview of operations research techniques used over the last ten years to improve the efficiency of renewable energy systems. Renewable energy systems are getting more complex. We urgently need to switch to sources quickly. As a result, this field has seen advancements in both applying and researching techniques. Operations research techniques play a role in this. They help optimize energy systems. The study covers techniques. These have been applied to enhance efficiency. Renewable energy systems are vital. They help reduce our reliance on -renewable sources. The study highlights developments. These have occurred over the past decade.

Although logical and simulation methods work well for nonlinear situations, mathematical programming methods, especially hybrid linear and probabilistic programming are still the main way to improve green energy, some advanced studies might combine these methods with machine learning and data-driven approaches to make energy even better, these approaches, including programming can help make green energy more efficient. The use of machine learning and data-driven methods can also improve the results of energy projects. Mathematical programming, machine learning and data-driven approaches all play a role, in advancing energy.

The energy systems have grown from the usual power generation design and grid management to include areas like energy trading between people, transportation systems that work together and concerns, about the circular economy. This change shows how the energy systems are changing and how the big environmental problems that the energy systems try to solve are also changing. The energy systems are really. The energy systems are trying to solve new environmental problems.

There are still problems, with this. We have to figure out what we know and what we do. People also get confused because things are not clear. It is hard to do things with computers because it is complicated. Even though we have made a lot of progress we still have to do research on algorithms and design techniques. Algorithm research is important. We also need people from fields to work together like professors and professionals to make algorithms better. Computer technology and data analysis are really important for making energy work. We need to understand a lot, about this area to make it happen. Renewable energy systems are all connected so we have to look at the picture and find the best way to do things. As we figure out how to make energy work, we will need to use special techniques to plan and run things smoothly. This will help us make the decisions and move forward with sustainable energy.

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