

Renewable Energy Optimization Using Intelligent Computational Methods

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Abstract

The increasing integration of renewable energy into modern power systems has created new requirements for intelligent optimization, forecasting, energy management, and grid coordination. Solar, wind, hydropower, biomass, and other renewable sources are inherently influenced by environmental variability, creating challenges for reliable generation, storage, scheduling, demand balancing, and economic operation. Intelligent computational methods can address these challenges by processing large datasets, forecasting renewable generation, optimizing resource allocation, managing energy storage, and supporting adaptive power-system operation. This study examines renewable energy optimization using intelligent computational methods through a conceptual and descriptive research approach. The study focuses on artificial intelligence, machine learning, deep learning, evolutionary algorithms, swarm intelligence, fuzzy logic, reinforcement learning, predictive analytics, and hybrid optimization techniques. Their applications in renewable-generation forecasting, energy-storage scheduling, microgrid management, demand response, distributed energy resources, grid integration, and energy-cost optimization are examined.

An integrated framework is developed connecting renewable-resource assessment, data acquisition, preprocessing, intelligent forecasting, optimization, storage management, grid coordination, and continuous performance evaluation. The analysis indicates that intelligent computational methods can improve forecasting accuracy, operational flexibility, energy utilization, storage scheduling, and resource allocation. However, implementation involves challenges associated with data quality, computational complexity, algorithm selection, uncertainty, cybersecurity, interoperability, infrastructure costs, and technical expertise. Intelligent optimization should therefore be integrated with physical energy-system constraints, grid requirements, regulatory frameworks, and sustainability objectives. Future research should investigate explainable AI, physics-informed machine learning, digital twins, federated learning, edge intelligence, autonomous microgrids, hybrid renewable-storage optimization, and climate-aware energy forecasting. The proposed framework provides a structured basis for developing intelligent, efficient, flexible, reliable, and sustainable renewable-energy systems capable of supporting the transition toward low-carbon energy infrastructures.

Keywords: Renewable Energy, Energy Optimization, Artificial Intelligence, Machine Learning, Computational Intelligence, Smart Grid, Energy Storage, Renewable Forecasting, Microgrids, Sustainable Energy

1. Introduction

The global transition toward sustainable energy systems has increased the importance of renewable energy technologies. Solar, wind, hydropower, biomass, and other renewable sources can contribute to reducing dependence on finite fossil-fuel resources and supporting lower-emission energy systems. However, renewable generation is influenced by weather conditions, seasonal patterns, geographical characteristics, and resource availability. These variations create operational challenges for electricity generation, storage, grid balancing, and demand management.

Traditional energy-management approaches were generally designed around relatively predictable and centralized generation systems. The growing deployment of variable renewable resources has increased the need for more flexible computational approaches capable of responding to rapidly changing generation and demand conditions. Modern energy systems generate large amounts of data through smart meters, weather stations, sensors, power converters, energy-management systems, and distributed energy resources. Intelligent computational methods can transform these data into information for forecasting and optimization.

Machine learning and artificial intelligence can support renewable-energy forecasting by identifying relationships between environmental conditions and generation output. Solar-power forecasting can incorporate solar radiation, temperature, cloud conditions, and historical generation data, while wind-power forecasting can incorporate wind speed, direction, atmospheric conditions, and turbine characteristics. Deep-learning models can process complex temporal and nonlinear relationships, providing additional forecasting capabilities for energy-management systems.

Optimization is another important application of computational intelligence. Energy systems must frequently determine how available renewable generation, storage systems, conventional resources, and electricity demand should be coordinated. Evolutionary algorithms, swarm-intelligence methods, fuzzy systems, mathematical optimization, and reinforcement learning can address different optimization problems. These approaches can support generation scheduling, battery operation, demand response, microgrid management, and distributed-energy coordination.

Energy storage plays a central role in renewable integration. Batteries and other storage technologies can absorb excess renewable generation and release energy when generation is insufficient. Intelligent optimization can determine charging and discharging schedules according to generation forecasts, demand patterns, electricity prices, battery conditions, and grid requirements. Appropriate optimization can support efficient storage utilization while considering technical constraints and battery degradation.

Microgrids provide another important environment for intelligent energy optimization. A microgrid may integrate renewable generators, storage, controllable loads, and conventional resources within a coordinated system. Intelligent controllers can dynamically balance supply and demand and support different operating conditions. Reinforcement learning and hybrid optimization methods may enable adaptive control while incorporating operational constraints.

Demand-side management can also benefit from computational intelligence. Smart meters and connected devices can provide information about consumption patterns. Intelligent algorithms can help schedule flexible loads, coordinate electric vehicles, optimize heating and cooling, and shift demand

according to renewable availability. Such approaches can improve alignment between electricity consumption and variable renewable generation.

The environmental and economic dimensions of renewable-energy optimization should also be considered. Optimization objectives may include energy efficiency, operating cost, renewable utilization, storage performance, emissions reduction, reliability, and grid stability. Multi-objective computational methods can examine trade-offs among these objectives. However, optimization results remain dependent on assumptions, data quality, system constraints, and the selected objective functions.

2. Objectives of the Study

2.1 Primary Objective

The primary objective of this study is to examine intelligent computational methods for renewable-energy optimization by analyzing how artificial intelligence, machine learning, deep learning, evolutionary algorithms, swarm intelligence, fuzzy logic, reinforcement learning, predictive analytics, and hybrid optimization can improve renewable forecasting, energy-storage management, grid integration, demand response, operational efficiency, and sustainable energy utilization.

2.2 Examination of Intelligent Computational Methods

The first objective is to examine computational methods applicable to renewable-energy optimization, including machine learning, deep learning, evolutionary algorithms, particle-swarm optimization, fuzzy logic, reinforcement learning, predictive analytics, and hybrid intelligent models. The study considers their applications in solar and wind forecasting, energy-storage scheduling, microgrid control, demand management, distributed-energy coordination, and renewable-generation optimization. Particular attention is given to forecasting performance, optimization capabilities, computational requirements, adaptability, uncertainty, and integration with physical energy-system constraints.

2.3 Analysis of Renewable Energy Optimization Applications

The second objective is to analyze how intelligent computational methods can improve renewable-energy utilization, storage scheduling, demand response, microgrid operation, grid balancing, and energy-cost management. The study also examines challenges involving data quality, computational complexity, uncertainty, interoperability, cybersecurity, infrastructure investment, technical expertise, and algorithmic transparency. The objective is to develop an integrated optimization perspective that combines computational intelligence with renewable-resource availability, energy-system requirements, economic considerations, and sustainability objectives.

3. Review of Literature

3.1 Intelligent Computing in Renewable Energy

Artificial intelligence and computational intelligence have become important tools for renewable-energy analysis because they can identify nonlinear relationships and process large datasets. Machine-learning techniques support forecasting and classification, while optimization algorithms can evaluate alternative operational configurations. These approaches are increasingly relevant to solar, wind, storage, microgrid, and smart-grid applications.

3.2 Renewable Energy Forecasting

Forecasting renewable generation is important because solar and wind resources vary according to environmental conditions. Machine-learning and deep-learning models can use historical generation, weather observations, and operational data to estimate future output. Accurate forecasts can support scheduling, storage operation, demand response, and grid balancing. Hybrid forecasting models can combine multiple computational techniques.

3.3 Intelligent Optimization and Energy Storage

Optimization methods can support decisions regarding generation scheduling, battery charging and discharging, load management, and microgrid operation. Evolutionary and swarm-intelligence methods can solve complex optimization problems, while reinforcement learning can support adaptive decision-making. Multi-objective approaches can consider cost, efficiency, renewable utilization, reliability, and environmental performance simultaneously.

4. Research Methodology

4.1 Research Design

This study adopts a conceptual and descriptive research design to examine intelligent computational methods for renewable-energy optimization. The study synthesizes concepts related to artificial intelligence, machine learning, deep learning, evolutionary computation, swarm intelligence, fuzzy logic, reinforcement learning, renewable forecasting, energy storage, microgrids, demand response, and smart-grid management.

The framework considers relationships among renewable-resource availability, data acquisition, forecasting, optimization, storage, demand, grid coordination, and sustainability. A conceptual design supports systematic analysis without introducing unsupported empirical observations or fabricated experimental results.

4.2 Literature Collection and Thematic Organization

The literature was conceptually organized around renewable-energy forecasting, intelligent optimization, computational intelligence, solar and wind systems, energy storage, microgrids, demand response, distributed energy resources, and smart grids. The reviewed concepts were grouped into resource assessment, data processing, forecasting, optimization, storage management, grid coordination, and performance evaluation.

Additional attention was given to uncertainty, algorithmic complexity, interoperability, cybersecurity, infrastructure requirements, computational efficiency, and technical expertise. This thematic organization provided the basis for constructing an integrated intelligent renewable-energy optimization framework.

4.3 Analytical Framework

The analytical framework includes:

- **Renewable Resource Assessment:** Evaluation of solar, wind, hydro, biomass, and other renewable resources.

- **Data Acquisition:** Collection of weather, generation, demand, storage, and grid information.
- **Data Preprocessing:** Cleaning, normalization, feature engineering, and quality assessment.
- **Renewable Forecasting:** Prediction of solar and wind generation.
- **Machine Learning:** Identification of patterns and predictive relationships.
- **Deep Learning:** Analysis of complex temporal and nonlinear energy datasets.
- **Evolutionary Optimization:** Search for efficient energy-system configurations.
- **Swarm Intelligence:** Optimization of generation, storage, and scheduling.
- **Fuzzy Logic:** Management of uncertainty and rule-based energy decisions.
- **Reinforcement Learning:** Adaptive energy-management decisions.
- **Energy Storage Optimization:** Intelligent charging and discharging.
- **Demand Response:** Alignment of consumption with renewable availability.
- **Microgrid Management:** Coordination of distributed energy resources.
- **Grid Integration:** Balancing renewable generation and system requirements.
- **Multi-Objective Optimization:** Simultaneous consideration of cost, efficiency, reliability, and sustainability.
- **Performance Evaluation:** Assessment of energy, economic, technical, and environmental outcomes.

4.4 Data Analysis Approach

A thematic analytical approach was applied to examine relationships among intelligent computational methods and renewable-energy management functions. Applications were categorized into forecasting, optimization, storage management, demand response, microgrid operation, and grid integration. Computational methods were assessed according to their potential contribution to prediction accuracy, operational flexibility, renewable utilization, cost management, and system reliability.

The analysis also considered uncertainty, data quality, computational complexity, interoperability, cybersecurity, and technical capacity. The synthesis informed development of an integrated framework for intelligent renewable-energy optimization.

5. Analysis

5.1 Intelligent Computational Methods for Renewable Energy

Table 1: Computational Methods and Renewable-Energy Applications

Computational Method	Primary Function	Renewable-Energy Application
Linear Regression	Prediction	Solar generation forecasting
Decision Trees	Classification	Energy condition assessment
Random Forest	Prediction	Wind and solar forecasting
Neural Networks	Nonlinear prediction	Renewable generation
Deep Learning	Complex forecasting	Time-series energy prediction

Computational Method	Primary Function	Renewable-Energy Application
Fuzzy Logic	Rule-based control	Energy management
Genetic Algorithms	Optimization	System configuration
Particle Swarm Optimization	Optimization	Storage scheduling
Reinforcement Learning	Adaptive control	Microgrid management
Hybrid AI Models	Integrated prediction	Renewable-grid optimization

The methods in Table 1 provide complementary capabilities for renewable-energy systems. Regression and tree-based models can support structured prediction, while neural networks and deep-learning approaches can process complex nonlinear and temporal information. Genetic algorithms and particle-swarm optimization can search for efficient system configurations and operational schedules.

Fuzzy logic can support decisions under uncertainty, while reinforcement learning can enable adaptive control. Hybrid approaches can combine forecasting and optimization capabilities for more integrated energy-management applications.

5.2 Renewable Energy Optimization Applications

Table 2: Application Areas and Optimization Functions

Application Area	Optimization Function	Expected Management Contribution
Solar Energy	Generation forecasting	Improved scheduling
Wind Energy	Output prediction	Grid coordination
Battery Storage	Charge/discharge scheduling	Improved storage utilization
Microgrids	Resource coordination	Operational flexibility
Demand Response	Load scheduling	Demand-generation alignment
Smart Grids	Power balancing	Grid management
Electric Vehicles	Charging optimization	Flexible demand
Hybrid Systems	Resource allocation	Renewable utilization
Energy Markets	Cost optimization	Economic operation
Distributed Energy	Local coordination	System flexibility

Intelligent computational methods can support renewable-energy optimization across multiple operational contexts. Solar and wind forecasting can provide information for scheduling, while storage

optimization can coordinate battery charging and discharging. Microgrid optimization can integrate distributed generators and flexible loads.

Demand-response systems can align electricity consumption with renewable availability. Electric-vehicle charging can become a flexible demand resource when appropriately managed. Hybrid renewable systems can use optimization to coordinate multiple generation and storage technologies under operational constraints.

6. Discussion

6.1 Intelligent Forecasting and Renewable Generation Management

Renewable-energy forecasting is an important application of intelligent computational methods because solar and wind generation can vary substantially with environmental conditions. Machine-learning and deep-learning models can analyze historical generation, weather observations, and operational variables to estimate future renewable output. Forecast information can subsequently support generation scheduling, storage management, demand response, and grid balancing.

Forecasting performance depends on data quality, temporal resolution, geographical characteristics, and changing weather conditions. Models developed for one location may not automatically perform similarly elsewhere. Combining data-driven models with physical knowledge and meteorological information can improve robustness. Forecast uncertainty should also be communicated to energy managers because predicted renewable output represents an estimate rather than a guaranteed generation level.

6.2 Optimization of Storage, Microgrids, and Demand

Intelligent optimization can coordinate renewable generation with energy storage and electricity demand. Battery systems can be scheduled to absorb excess renewable energy and discharge during periods of insufficient generation. Optimization models can incorporate electricity demand, renewable forecasts, battery constraints, and operational objectives. In microgrids, intelligent methods can coordinate renewable generators, storage, controllable loads, and other distributed resources.

Demand response provides another optimization opportunity. Flexible loads can potentially be scheduled during periods of higher renewable availability, reducing the mismatch between generation and consumption. Electric-vehicle charging can also be coordinated with renewable generation and grid requirements. These strategies require careful consideration of user requirements, technical constraints, battery conditions, and electricity-system reliability. Intelligent algorithms should therefore operate within defined physical and operational boundaries.

6.3 Multi-Objective Optimization and Sustainable Energy Systems

Renewable-energy optimization frequently involves multiple objectives rather than a single target. System operators may seek to improve renewable utilization while reducing operating costs and maintaining reliability. Storage degradation, emissions, system losses, power quality, and infrastructure constraints may also need to be considered. Multi-objective optimization can evaluate alternative solutions and identify trade-offs among competing objectives.

Computational intelligence can provide flexible approaches for addressing these complex decision problems. However, optimization outcomes depend on the objective functions and constraints defined by system designers. An algorithm may optimize a selected mathematical objective without representing every relevant environmental or social consideration. Sustainable energy optimization should therefore incorporate appropriate technical, economic, environmental, and regulatory requirements. Human oversight remains important when computational outputs inform consequential energy-management decisions.

7. Challenges

7.1 Data Quality and Renewable Variability

Renewable-energy optimization depends on accurate information about generation, weather, demand, storage, and grid conditions. Data can contain missing observations, sensor errors, inconsistent measurements, and changes in operating conditions. Renewable generation is also influenced by weather variability that can be difficult to predict precisely. These factors can affect forecasting and optimization performance.

Models trained on historical datasets may encounter conditions that were not represented during training. Seasonal changes, extreme weather, equipment degradation, and changes in energy demand can alter model behavior. Continuous validation and model updating are therefore important. Combining multiple data sources and incorporating uncertainty estimates can strengthen the reliability of intelligent energy-management systems.

7.2 Computational Complexity and Algorithm Selection

Advanced optimization problems can involve numerous variables and constraints, particularly in large power systems with distributed generation, storage, electric vehicles, and flexible loads. Computational complexity can increase when multiple objectives must be optimized simultaneously. Different algorithms may also produce different solutions depending on parameter settings, objective functions, and system constraints.

Selecting an appropriate computational method therefore requires consideration of problem characteristics, available computational resources, response time, scalability, and accuracy. Hybrid algorithms can combine complementary methods but may increase system complexity. Model benchmarking, sensitivity analysis, validation, and transparent reporting of optimization assumptions are important for evaluating computational performance and practical applicability.

7.3 Cybersecurity, Interoperability, and Infrastructure

Intelligent renewable-energy systems increasingly depend on connected sensors, communication networks, cloud platforms, smart meters, and automated controllers. Greater connectivity can increase exposure to cybersecurity threats. Unauthorized access, data manipulation, communication failures, or system disruptions can affect energy operations. Appropriate authentication, encryption, monitoring, access controls, and cybersecurity procedures are therefore important.

Interoperability is another challenge because renewable-energy systems may contain equipment from different manufacturers and technological generations. Integrating intelligent optimization with

existing grid infrastructure can require compatible communication protocols and data formats. Infrastructure investment is also necessary for sensors, storage, communication systems, computing platforms, and control technologies. Successful implementation requires technical expertise, maintenance, standardized interfaces, and long-term planning.

8. Future Research

Future research should investigate physics-informed and uncertainty-aware machine-learning models for renewable-energy forecasting. These approaches could combine physical principles with historical energy and meteorological data to improve model robustness. Research should examine advanced forecasting for solar irradiance, wind generation, hybrid renewable systems, and extreme weather conditions. Additional studies could investigate probabilistic forecasting methods that provide prediction ranges rather than single values, enabling energy managers to incorporate uncertainty more effectively into storage, scheduling, and grid-balancing decisions.

Future studies should explore intelligent digital twins for renewable-energy systems, microgrids, battery storage, and distributed energy networks. Digital twins could combine real-time operational data with simulation and optimization to evaluate alternative control strategies before deployment. Research should examine reinforcement learning for adaptive storage management, coordinated electric-vehicle charging, demand response, and autonomous microgrid operation. Federated learning and edge intelligence could also be investigated to support distributed analytics while reducing communication requirements and potentially improving data-management capabilities.

Future research should develop multi-objective optimization frameworks that simultaneously consider renewable utilization, system reliability, operating cost, storage degradation, emissions, infrastructure requirements, and lifecycle sustainability. Researchers should also evaluate the energy and environmental costs of computational intelligence itself, particularly for large-scale AI systems. Standardized benchmarking frameworks could compare algorithms across renewable technologies, climatic conditions, and system configurations. Human-centered interfaces should further be developed so that energy operators can interpret optimization recommendations, uncertainty information, and system constraints before implementing computationally generated strategies.

9. Conclusion

Intelligent computational methods provide important opportunities for optimizing renewable-energy systems under increasingly complex operating conditions. Artificial intelligence, machine learning, deep learning, evolutionary algorithms, swarm intelligence, fuzzy logic, reinforcement learning, and hybrid approaches can support renewable forecasting, energy-storage management, demand response, microgrid coordination, and grid integration. These methods can process large datasets and identify operational patterns that may support more responsive energy-management decisions.

Renewable-energy optimization should integrate forecasting with operational planning. Accurate information about solar and wind generation can support storage scheduling and demand management, while intelligent optimization can coordinate distributed energy resources. Batteries, electric vehicles, flexible loads, and microgrids can provide additional flexibility when managed appropriately. However,

computational solutions should operate within physical energy-system constraints, grid requirements, safety considerations, and established operational procedures.

Important challenges include renewable variability, data limitations, computational complexity, algorithm selection, cybersecurity, interoperability, infrastructure requirements, and technical expertise. Intelligent models should be continuously validated because energy systems and environmental conditions change over time. Optimization results should also be interpreted with appropriate uncertainty information. Combining data-driven approaches with physical energy-system knowledge can provide a stronger foundation for reliable and responsible renewable-energy optimization.

Future renewable-energy systems are likely to become increasingly intelligent, decentralized, interconnected, and adaptive. Physics-informed AI, digital twins, edge intelligence, federated learning, reinforcement learning, advanced storage optimization, and multi-objective computational methods can expand the capabilities of intelligent energy management. At the same time, sustainable optimization should consider technical performance, economic efficiency, environmental impacts, cybersecurity, and long-term system resilience. An integrated computational framework connecting forecasting, optimization, storage, demand, grid coordination, and continuous learning can support efficient and sustainable renewable-energy development.

References

1. Banos, R., Manzano-Agugliaro, F., Montoya, F. G., Gil, C., Alcayde, A., & Gómez, J. (2011). Optimization methods applied to renewable and sustainable energy: A review. *Renewable and Sustainable Energy Reviews*, 15(4), 1753–1766. <https://doi.org/10.1016/j.rser.2010.12.008>
2. Koutroulis, E., Kolokotsa, D., Potirakis, A., & Kalaitzakis, K. (2006). Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms. *Solar Energy*, 80(9), 1072–1088. <https://doi.org/10.1016/j.solener.2005.11.002>
3. Dufo-López, R., & Bernal-Agustín, J. L. (2005). Design and control strategies of PV-Diesel systems using genetic algorithms. *Solar Energy*, 79(1), 33–46. <https://doi.org/10.1016/j.solener.2004.10.004>
4. Yang, H., Zhou, W., Lu, L., & Fang, Z. (2008). Optimal sizing method for stand-alone hybrid solar–wind system with LPSP technology by using genetic algorithm. *Solar Energy*, 82(4), 354–367. <https://doi.org/10.1016/j.solener.2007.08.005>
5. Dufo-López, R., & Bernal-Agustín, J. L. (2008). Multi-objective design of PV-wind-diesel-hydrogen-battery systems. *Renewable Energy*, 33(11), 2559–2570.
6. Dufo-López, R., Bernal-Agustín, J. L., & Yusta-Loyo, J. M. (2009). Multi-objective optimization minimizing cost and life cycle emissions of stand-alone PV-wind-diesel systems with batteries storage. *Applied Energy*, 86(9), 1634–1643.
7. Dufo-López, R., Bernal-Agustín, J. L., & Contreras, J. (2007). Optimization of control strategies for stand-alone renewable energy systems with hydrogen storage. *Renewable Energy*, 32(7), 1102–1126. <https://doi.org/10.1016/j.renene.2006.04.013>
8. Fadaee, M., & Radzi, M. A. M. (2012). Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review. *Renewable and Sustainable Energy Reviews*, 16(5), 3364–3369. <https://doi.org/10.1016/j.rser.2012.02.071>

9. Kusiak, A., Zheng, H., & Song, Z. (2009). Short-term prediction of wind farm power: A data mining approach. *IEEE Transactions on Energy Conversion*, 24(1), 125–136. <https://doi.org/10.1109/TEC.2008.2006552>
10. Liu, Y., Shi, J., Yang, Y., & Han, S. (2009). Piecewise support vector machine model for short-term wind-power prediction. *International Journal of Green Energy*, 6(5), 479–489. <https://doi.org/10.1080/15435070903228050>
11. Boonbumroong, U., Pratinthong, N., Thepa, S., Jivacate, C., & Pridasawas, W. (2011). Particle swarm optimization for AC-coupling stand-alone hybrid power systems. *Solar Energy*, 85(3), 560–569. <https://doi.org/10.1016/j.solener.2010.12.027>
12. Mayer, M. J., Szilágyi, A., & Gróf, G. (2020). Environmental and economic multi-objective optimization of a household level hybrid renewable energy system by genetic algorithm. *Applied Energy*, 269, 115058. <https://doi.org/10.1016/j.apenergy.2020.115058>
13. Yu, S., You, L., & Zhou, S. (2023). A review of optimization modeling and solution methods in renewable energy systems. *Frontiers of Engineering Management*, 10, 640–671. <https://doi.org/10.1007/s42524-023-0271-3>
14. Ying, C., Wang, W., Yu, J., Li, Q., Yu, D., & Liu, J. (2023). Deep learning for renewable energy forecasting: A taxonomy, and systematic literature review. *Journal of Cleaner Production*, 384, 135414. <https://doi.org/10.1016/j.jclepro.2022.135414>
15. Abisoye, B. O., Sun, Y., & Zenghui, W. (2024). A survey of artificial intelligence methods for renewable energy forecasting: Methodologies and insights. *Renewable Energy Focus*, 48, 100529. <https://doi.org/10.1016/j.ref.2023.100529>
16. Li, Y., Ding, Y., He, S., Hu, F., Duan, J., Wen, G., Geng, H., Wu, Z., Gooi, H. B., Zhao, Y., Zhang, C., Mei, S., & Zeng, Z. (2024). Artificial intelligence-based methods for renewable power system operation. *Nature Reviews Electrical Engineering*, 1, 163–179. <https://doi.org/10.1038/s44287-024-00018-9>
17. Yang, Y., Lou, H., Wu, J., Zhang, S., & Gao, S. (2024). A survey on wind power forecasting with machine learning approaches. *Neural Computing and Applications*, 36, 12753–12773. <https://doi.org/10.1007/s00521-024-09923-4>
18. Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T.-C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy & Environment*, 35(7). <https://doi.org/10.1177/0958305X241256293>
19. Yousef, L. A., Yousef, H., & Rocha-Meneses, L. (2023). Artificial intelligence for management of variable renewable energy systems: A review of current status and future directions. *Energies*, 16(24), 8057. <https://doi.org/10.3390/en16248057>
20. Shams, M. B., et al. (2023). Sustainable energies and machine learning: An organized review of recent applications and challenges. *Energy*, 266, 126432. <https://doi.org/10.1016/j.energy.2022.126432>