



Review Article

Optimization Methods and Open-Source Frameworks for Renewable Energy Planning: A Systematic Review Focused on Open Energy Modelling Framework (OEMOF)

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ABSTRACT

Renewable energy systems are increasingly essential for sustainable development, yet their design and planning require robust optimization methods. This study is motivated by the need to understand how different optimization approaches and modelling tools support transparent and efficient energy strategies. The central aim is to evaluate whether specific optimization frameworks can be regarded as universally superior or whether their suitability depends on contextual factors. A systematic literature review was conducted by examining 54 peer-reviewed articles published between 2017 and 2025, covering linear programming, mixed-integer linear programming, metaheuristic algorithms, and models based on artificial intelligence, with a particular focus on open-source energy modelling frameworks. The results show that no single method consistently outperforms others, as effectiveness is strongly influenced by system complexity, data quality, and planning objectives. This leads to the conclusion that integrated deterministic and adaptive strategies are necessary for reproducible, transparent, and sustainable renewable energy modelling.

KEYWORDS

Open Energy Modelling Framework; Renewable energy planning; Optimization methods; Metaheuristic algorithms; Artificial intelligence models; Energy systems sustainability.

INTRODUCTION

Renewable energy systems are increasingly essential for sustainable development, yet their design and planning require robust optimization methods. In countries like Indonesia, recent reviews also emphasize that advanced modelling tools are crucial to support the transition towards net-zero emission systems, since they enable the integration of diverse resources and

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sectors in a coherent framework [1]. The global transition to a clean and sustainable energy system has become a top priority in national energy policies. The unlimited use of fossil fuels will contribute to environmental damage, thus encouraging countries to seek renewable energy-based solutions [2], [3]. In this context, new renewable energy resources such as solar, wind, hydro, and biomass are key in supporting the energy sector's decarbonization and achieving net-zero emissions targets. However, large-scale renewable energy integration also brings challenges like supply uncertainty, intermittency, and system flexibility. Planning that refers to the management of the national energy system is needed to optimize the energy transition. The shift towards renewable energy-based solutions also requires analytical approaches that can adequately represent the complexity of energy systems. Simulation modelling has been critically reviewed as an essential method to analyze and evaluate renewable energy integration and system behavior under different scenarios [4].

Recent studies published in the Journal of Sustainable Development of Energy, Water and Environment Systems (JSDEWES) have emphasized the importance of integrating optimization with sustainability assessments. For example, [5] explored multi-objective optimization for multi-energy systems, demonstrating the trade-offs between economic, environmental, and technical objectives. Similarly, [6] analysed temporal variability in long-term energy supply planning, while [7] applied bio-inspired metaheuristics to enhance renewable energy system performance. These contributions highlight the growing role of advanced optimization methods and open-source frameworks in supporting transparent and sustainable planning.

National Energy System Optimization Needs

Effective renewable energy planning requires optimization methods capable of handling the complexity of multi-sector and multi-location systems. Various approaches have been applied in the literature study, ranging from conventional mathematical techniques such as Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) to metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO) [8], [9]. These optimization techniques allow energy planners to develop the most efficient technology configuration based on cost, reliability, and environmental impact aspects.

Along with the development of digital technology and open resources, open-source software-based energy system modelling is also growing. One of the prominent frameworks is the Open Energy Modelling Framework (OEMOF), which offers a modular, transparent, and flexible approach to decentralized and national energy planning. OEMOF supports cross-sector integration (sector coupling), utilizes advanced optimization solvers, and encourages reproducible research practices in energy policy analysis [7]. The Open Energy Modelling Framework was introduced in 2017 as an open-source initiative supporting cross-sectoral and regional energy system modelling. The framework was initially developed by a consortium of research institutes in Germany—including the Reiner Lemoine Institute and IEE's Fraunhofer—to provide a modular, community-based alternative to proprietary software. OEMOF was first introduced through a preprint article by [10] and then reinforced in peer-reviewed scientific publications [11], which makes it one of the key platforms in open energy modelling.

Study Objectives: Method Classification, Comparative Analysis, and Focus on OEMOF

Although the number of studies on renewable energy systems continues to increase, systematic comparisons of optimization methods and open modeling tools used in different countries are still minimal. In particular, the role of OEMOF in national energy planning—both in developed and developing countries—has not been critically analyzed. Considering the context that has been described, this study is directed to conduct a systematic literature review

of optimization methods and open-source modeling platforms used in renewable energy planning at the national level.

Although several recent reviews have discussed renewable energy optimization methods (e.g., [8], [12], [13]), most of them primarily focus on algorithmic development or hybrid renewable system sizing. Likewise, reviews on energy system modelling tools such as [1] and [14] mainly classify models based on structural characteristics without critically examining the comparative applicability of open-source frameworks in national-level renewable energy planning. Furthermore, none of these reviews comprehensively integrate post-2022 developments in AI-based optimization and their interaction with deterministic frameworks such as OEMOF. Therefore, this study addresses this research gap by combining methodological comparison, national-scale application context, and framework-specific evaluation up to early 2025.

The primary focus is on:

- a. Identification and classification of commonly used optimization methods,
- b. Analysis of their application in the context of different national policies and conditions,
- c. Evaluation of the strengths and limitations of OEMOF as an energy planning tool.

Through this approach, this study is expected to contribute to expanding the understanding of methods in sustainable energy planning and to become an essential reference for policymakers, researchers, and developers of future energy systems.

Literature Search Strategy

The search was conducted using Publish or Perish from Google Scholar, Scopus, and Web of Science sources with keywords: "renewable energy," "open-source energy modeling," "OEMOF," "PyPSA," "Calliope," and "optimization," in the range of 2017–2025. The year 2017 was chosen as the starting point because it was the year the OEMOF framework was formally introduced in the academic literature.

Inclusion and Exclusion Criteria

For the reviewed articles to be relevant to the purpose of the study, the inclusion and exclusion criteria set out in [Table 1](#).

Table 1. Research inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed studies in reputable international journals	Conference articles without a thorough review
Focus on national or regional-scale energy systems	Studies limited to micro or household systems
Using optimization methods in energy planning	Articles that only discuss technology without planning aspects
Review or use open-source frameworks (e.g., OEMOF, PyPSA, etc.)	Articles that use exclusively closed commercial software

PRISMA LITERATURE AND DIAGRAM SELECTION PROCESS

The following is a PRISMA flowchart used to support the methodological part of this Systematic Literature Review (SLR) as shown as [Figure 1](#).

The literature selection process in this study follows the PRISMA approach, which is tailored for systematic studies related to renewable energy optimization and open-source modeling frameworks.

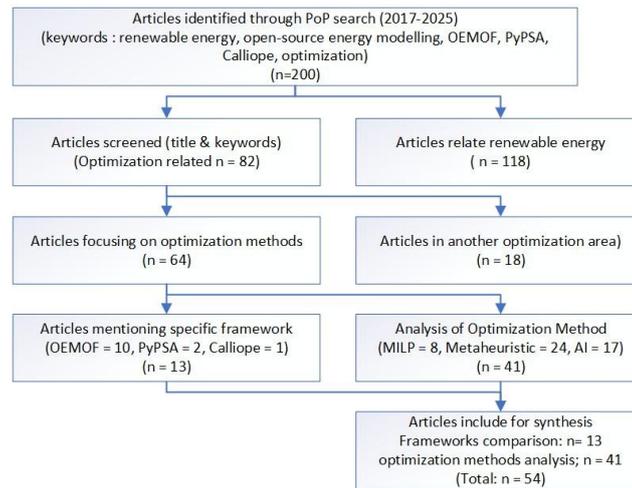


Figure 1. PRISMA Flow Diagram of Article Selection (2017–2025)

Out of 200 articles found, filtered by title and keyword, 82 articles were relevant to optimization topics. Furthermore, 64 articles focused on optimization methods, and 13 mentioned specific open-source frameworks. The analysis was continued on 41 articles that applied optimization methods (LP/MLP, metaheuristics, and artificial intelligence), and all of these articles were synthesized together with 13 framework articles, resulting in 54 articles used in the primary analysis. The total number of references in the bibliography reached 82, including other supporting literature.

Data Extraction and Analysis

Data from 82 articles that have passed the selection are then systematically extracted using a table format. Each article is analyzed based on the following information: author name and year, study location, type of renewable energy studied, optimization methods used, open-source modeling platform (if any), study objectives, main results, advantages, and limitations. The collected data is then used to classify optimization methods, compare countries, and identify research trends and gaps.

Validity and Limitations of Methods

Article selection was carried out following a predefined protocol aligned with PRISMA guidelines to maintain methodological rigor. Screening was conducted in three stages: (1) identification through database search, (2) title and abstract screening, and (3) full-text eligibility assessment.

Although the screening process was conducted by a single researcher, several mechanisms were applied to minimize subjective bias. First, inclusion and exclusion criteria were defined prior to the search process. Second, AI-assisted reference management tools were used to perform semantic clustering, keyword consistency checks, and duplication detection. Third, a random subset (approximately 15 %) of screened articles was re-evaluated after two weeks to ensure consistency in selection decisions.

RESULT AND DISCUSSION

Optimization techniques in energy planning with Linear Programming and Mixed-Integer Linear Programming (MILP) implementation

Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) are the most commonly used mathematical approaches in energy system planning, especially at national and regional scales. A recent review further underscores their importance while also highlighting

the development of diverse optimization models and solution techniques tailored to renewable energy applications [12]. This method allows optimization problem solving by linearly considering technical, economic, and environmental constraints and can handle integer variables to represent discrete decisions such as technology choices or generating units.

In the context of renewable energy planning, MILP is often used to determine the optimal system configuration based on the lowest total cost, highest energy efficiency, or minimal carbon emissions, for example, in the study of [16], which applies the MILP optimization method to design a hybrid energy system that supports the development of District Heating (DH) based on renewable energy in Gaziantep City, Turkey. The MILP approach determines the optimal capacity of various energy system components, including solar (PV) plants, wind turbines, heat pumps, and thermal storage, to minimize the Levelized Cost of Energy (LCOE). This model considers various variables such as investment costs, operating and maintenance costs, equipment replacement cycles, and carbon dioxide emissions to meet heat energy demands efficiently. The optimization results showed that the best system configuration consisted of 560 MW PV and 65 MW of wind power, which produced an LCOE of USD 0.0442/kWh. The study compares MILP results with simulation tools such as HOMER and EnergyPLAN, and concludes that the MILP approach provides a more cost-effective and scalable energy planning solution in the context of renewable district heating systems.

The study [17] applied the MILP method to design a hybrid energy system consisting of wind turbines, diesel generators, and Battery-based Energy Storage Systems (BESS). Recent literature has also provided a comprehensive review of configuration optimization in hybrid renewable energy systems (HRES), emphasizing how different approaches can be applied to balance technical, economic, and environmental objectives [18]. In addition, a more recent review further highlights how technical, economic, and environmental criteria are jointly considered in HRES design and operation, providing a broader perspective on system integration [13]. In this context, energy storage has become a critical component of hybrid renewable energy systems. Bamisile [19] highlights that various optimization techniques have been developed to improve its efficiency, reliability, and cost-effectiveness. HRES often combine multiple resources to improve sustainability and reliability. Solar–wind combinations, in particular, have been widely reviewed as a promising configuration to balance intermittency and ensure stable supply in diverse contexts [20]. Beyond conventional storage solutions, hydrogen-based hybrid energy systems have also received significant attention, with recent reviews highlighting diverse optimization strategies to enhance their performance and cost-effectiveness [21].

The main objective of implementing the MILP is to determine the most optimal system configuration in terms of cost and performance, considering various commercial wind turbine technologies with different technical characteristics. This optimization model is used in two scenarios, namely the selection of one type of best turbine and a combination of multi-technology wind turbines, to capture variations in wind speed throughout the year. The optimization results showed that the multi-turbine approach reduced the total cost (Net Present Cost) by up to 4.5 % compared to the single-technology approach and improved renewable energy penetration and overall system efficiency. Thus, MILP is used as a strategic planning tool to design renewable energy systems that are economical, adaptive, and sustainable.

Peterssen [22] implemented the Linear Programming (LP) method for designing a carbon-neutral German national energy system by 2045. LP determines the design and operation of energy systems at the minimum total cost based on the assumption that all future conditions—weather and energy demand—can be perfectly predicted. This model optimizes generation capacity (such as PV and wind), energy storage size (battery, hydrogen, thermal), and energy distribution across sectors (transportation, heating, industry). The LP approach in this study serves as a theoretical baseline, which is then compared with the priority list method without forecasting, and the results showed that LP-based systems had a 28 % lower total cost.

The main advantages of LP and MILP lie in their computational stability and ability to provide optimal global solutions, provided that the model formulation is correct. Additionally, both methods are compatible with various optimization software, including open-source platforms such as OMOF and PyPSA. However, one of the limitations of MILP is the increased computational complexity as the number of integer variables increases, making it unsuitable for very large-scale models with high temporal dynamics. LP and MILP remain important cornerstones in energy system modeling due to their deterministic and interpretive nature. Its combination with an open-source framework provides flexibility in simulating transparent and replicable national energy policies.

Metaheuristic algorithm

Metaheuristic algorithms are a global search-based optimization approach widely used in energy system planning, especially for complex, non-linear, and multiobjective problems. In contrast to mathematical methods such as LP and MILP, which require linear and deterministic formulations, metaheuristics are more flexible in dealing with uncertainty, irregularity, and dynamic policy scenarios.

Some of the algorithms that are often used include Genetic Algorithm (GA) [23], [24], Multiobjective Genetic Algorithm (MOGA) [25], Particle Swarm Optimization (PSO) [26]–[29], Grey Wolf Optimizer (GWO) [8], [9], [30]–[36] as well as other hybrid algorithms. This algorithm can explore a wide range of solution spaces to find the optimal configuration of the energy system based on [37] several criteria, such as cost, emissions, and reliability. For distributed hybrid power systems, optimization methods are increasingly focusing on the integration of battery storage, as highlighted by Barbossa *et al.* [38], who demonstrate that storage considerations significantly influence both cost efficiency and system reliability.

A study by Frimpong, [31], [39], introduced the Social Spider Prey (SSP) algorithm, a new algorithm inspired by the social behavior of spiders in prey hunting. SSP is used to design hybrid energy systems with optimal sizing in mind, cost efficiency, and increased reliability. The study results show that this approach provides more stable results than conventional algorithms such as PSO and GA.

Meanwhile, metaheuristic algorithms include COOT, Black Widow Optimization (BWO), and Tasmanian Devil Optimization (TDO). [40]. This research shows that no single algorithm is universally superior in all scenarios, so the choice of algorithm is highly dependent on the type of system, the number of variables, and the optimization goals. GWO, for example, excels in rapid convergence on off-grid energy system configurations, while GA is more flexible in multi-constraint problems.

Metaheuristics are often combined with data-driven approaches, such as machine learning, to improve adaptivity to changing demand patterns or the variability of renewable resources. [41] proposes a hybrid approach that combines metaheuristic algorithms with machine learning models to deal with weather uncertainties in decentralized energy systems.

The main advantage of metaheuristic algorithms is their ability to efficiently solve non-convex and multiobjective problems, especially when deterministic methods become impractical due to the complexity of the model. However, its limitation lies in its heuristic search-based nature, so the results do not always guarantee global optimality or sensitivity to the initial parameters and evaluation functions used. Thus, metaheuristic algorithms provide high flexibility in developing national energy systems, especially when combined with dynamically changing environmental policy and data scenarios.

Artificial Intelligence Approach

In recent years, artificial intelligence (AI)-based approaches have become increasingly popular in energy system planning and prediction, especially in dealing with complexity, uncertainty, and large volumes of data. Recent reviews on modelling variable renewable energy

(VRE) sources such as solar and wind further emphasize the importance of developing advanced approaches that can capture intermittency and variability in system behaviour [42]. According to Mahmood et al. [43], the rapid digitalization of smart grids and renewable energy systems has further strengthened the role of AI by enabling real-time data processing and improving overall system efficiency. Techniques include Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM).

ANN is one of the earliest and most widely used AI approaches in the energy context. ANN can study the non-linear relationship patterns between inputs and outputs, making it particularly suitable as an intelligent prediction tool to support the operational efficiency of time-series data-based thermal energy systems [37]. The study evaluated various ANN architectures, including Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM), to determine the most accurate approach in the context of hybrid energy systems. The results show that ANN has advantages in handling data uncertainty and providing better predictions than conventional statistical methods.

Thus, ANN is essential in improving the accuracy of estimating renewable energy potential, a crucial input for hybrid energy systems' planning and operation process. Beyond forecasting, recent research has also explored the application of advanced AI methods for the sizing of hybrid renewable energy systems, showing how such techniques can optimize system configuration by balancing cost, reliability, and environmental performance [45].

In addition to ANN, the Support Vector Machines (SVM) algorithm predicts the daily electrical load going forward [46]. SVM has superior performance in predicting electricity usage in various settings, including educational institutions and supermarkets, and outperforms other models, such as Random Forest and Decision Trees, in terms of accuracy and efficiency [47].

LSTMs, as part of RNNs, excel at processing time series data such as renewable energy production that are volatile and seasonal. In the study [48], LSTM is used to predict river flows as a source of hydro energy, and it shows higher accuracy than other methods, such as the feedforward neural network (FFNN) and support vector regression (SVR).

The main advantage of the AI approach lies in its ability to learn from data and adapt to changing patterns without the need for explicit mathematical formulations. This makes AI suitable for data-driven national energy planning, especially when combined with sensor systems and real-time measurements. However, this approach also has limitations, such as the need for extensive, high-quality training data, the risk of overfitting, and the limited interpretability of the results.

The integration of AI in energy planning systems is often combined with other optimization methods, either hybrid with metaheuristics or as part of decision-support systems. With the increasing availability of energy, weather, and socio-economic data, AI approaches are expected to be increasingly important in supporting energy transition policies nationally and regionally. Given these methodological characteristics, a structured technical comparison is necessary to clarify the relative strengths and limitations of each approach.

Technical Comparison: Accuracy, Robustness, and Runtime

Each optimization approach in national energy planning has technical advantages and limitations that need to be considered based on the context of its application. In this regard, Laveneziana et al. [49] conducted a critical review of energy planning models for the industrial systems transition, highlighting their strengths, limitations, and the need for more adaptable frameworks. Three essential aspects commonly used to evaluate method performance are solution accuracy, robustness, and compute runtime.

Regarding accuracy, deterministic methods such as Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) can provide optimal solutions globally, as long as the model is formulated with objective functions and linear constraints and definitively known parameters. This makes MILP highly accurate for energy planning models with clear

mathematical structures, deterministic parameters, and linear relationships between system components. However, its accuracy may decrease if used on highly non-linear or high-uncertainty systems, as MILPs are not designed to handle random variables or complex relationships without a looping process that can compromise model precision [50].

In contrast, metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO) have the power to explore a wide range of solutions but often only guarantee a near-optimal solution. Their main advantage is the flexibility in handling various function objectives and constraints, but their accuracy is highly dependent on tuning parameters and convergence strategies [31], [8].

From a robustness perspective, AI-based approaches such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) excel in dealing with non-deterministic and dynamically changing data. ANNs and LSTMs can learn from historical data and update predictions adaptively, making them particularly useful for highly variable systems, such as wind and solar energy [51]. However, AI tends to be a black box that is less transparent in explaining decision logic and is highly dependent on the quality and volume of training data.

Meanwhile, from the computational runtime aspect, LP and MILP methods are relatively efficient for small to medium-scale models, especially when using optimization solvers such as CPLEX or Gurobi [52], [53]. However, the computation time will increase exponentially as the number of integer variables increases. On the other hand, metaheuristic algorithms take longer to converge, primarily when used for scenarios with many parameters and objectives. The AI approach requires significant initial training time, but the model can generate predictions quickly and vertically once trained.

Overall, no single method excels in all aspects. The selection of optimization methods is highly dependent on specific objectives, system structure, data availability, and computing resources. Therefore, some studies propose a hybrid approach combining the strengths of two or more methods, e.g., integrating MILP with LSTM for long-term planning based on dynamic demand predictions. The comparative characteristics and applicability of each technique, including their limitations and potential hybrid uses, are summarized in [Table 2](#).

Influence of Time-Series Data Availability on Model Selection

The availability and quality of time-series data play a critical role in determining the suitability of optimization methods for national energy planning. Deterministic approaches such as MILP require high-resolution temporal data (e.g., hourly load demand, renewable generation profiles, and storage dynamics) to produce reliable optimization outcomes. In countries with comprehensive energy monitoring systems, such models can accurately capture seasonal variability and system constraints.

In contrast, in contexts where historical data are incomplete, inconsistent, or limited in temporal resolution, AI-based models may offer greater adaptability. Techniques such as ANN and LSTM can approximate nonlinear relationships and generate forecasts even when physical system parameters are partially unknown.

Therefore, the selection between deterministic and AI-based methods is not purely methodological but strongly dependent on data maturity, digital infrastructure, and institutional capacity. Hybrid approaches integrating MILP for structural planning and AI for dynamic forecasting are increasingly emerging as robust solutions in data-transitioning economies.

Distribution of Methods by Country and Purpose of Use

Recent bibliometric reviews provide additional evidence on how optimization methods are distributed globally, showing clear regional trends in renewable energy system modelling [70]. Countries such as Germany, the Netherlands, and Denmark tend to use deterministic approaches such as MILP and LP in national energy modeling that are multi-sectoral and integrated [65]. The use of frameworks such as OEMOF and PyPSA is widespread in Germany

due to their compatibility with open-access data and flexibility in analyzing various energy transition scenarios [71].

Table 2. Summary of comparative optimization methods in energy planning

Method	Example Algorithm	of Superiority	Limitations	Accuracy	Runtime & Robustness	Key Reference
Linear Programming (LP) & MILP	MILP CPLEX Gurobi	The global, transparent optimal solution, suitable for deterministic models	Less flexible for non-linear dynamic systems	High (on linear & systems)	Fast for small-medium models; less robust against uncertainty	[16], [50], [54], [52], [53]
Metaheuristics	GA PSO GWO SSP	Flexible and able to handle many non-linear parameters functions	Results are not always optimal; they are sensitive & to tuning parameters	Medium-high (depending on configuration)	Medium-high runtime; more robust to variation	[55], [56], [23], [27], [34], [57], [29], [25], [36], [26], [28], [29], [31], [57], [58], [61], [27], [36], [40], [31], [39]
Artificial Intelligence	ANN SVM, LSTM	Adaptive, suitable for data fluctuations	It takes many big data and hard-to-interpret results (black box)	High (if data is quality)	Slow training, fast prediction; Very robust on dynamic data	[11], [37], [41], [44], [47], [55], [58], [62], [69], [28], [58], [37], [44], [48], [63], [64]

For example, a researcher [72] implemented OEMOF to model and optimize renewable energy-based heat supply systems in suburban Germany, focusing on technical and economic efficiency. The framework allows for the flexible formulation of multi-generator systems in linear equations optimized using the MILP approach to achieve cost-effective and low-carbon heat distribution.

On the other hand, developing countries like India [26], [73], [74], [75], Pakistan [51], [76], [77], Iran [78], [79], [34], [80], and some African countries [30], [81], [82], [83] tend to adopt optimization methods that are more flexible and tolerant of data limitations, such as metaheuristics (GA, PSO, GWO). This approach is considered more straightforward to implement, does not require complex mathematical structures, and can adapt to the variability of local conditions.

Studies by [84] [85] prove this approach's effectiveness in designing renewable energy systems for remote areas facing limited geographical and infrastructure challenges. Some studies have also adopted hybrid or rule-based models to improve the accuracy of planning decisions.

In addition to geographical differences, the primary purpose of applying optimization methods is also a determining factor in selecting techniques. The review found three common patterns:

1. Cost and emissions optimization: Become a priority in countries with ambitious climate targets like the European Union. Studies in this region tend to use deterministic and integrative approaches.
2. Expansion of energy access and village electrification: Dominating in developing countries is still facing the challenge of electrification in remote areas. These studies generally use metaheuristic methods or rule-based models because of their simplicity.
3. Improved reliability and flexibility of systems: Be focused on countries with high integration of renewable energy and innovative grid systems, where hybrid or AI-based methods are more widely used.

This distribution shows that no method is universal. The choice of method is highly dependent on the contextual needs, technical capacity, and direction of each country's national energy policy.

Renewable Energy Planning from the Perspective of Economic Scale and Energy Consumption

The selection of optimization methods is also influenced by the economic scale and total energy consumption of each country. Developed economies such as Germany and Denmark exhibit high total primary energy demand and advanced data infrastructure, enabling the use of deterministic MILP-based national energy system models.

In contrast, developing countries with lower GDP per capita and limited grid coverage often prioritize decentralized hybrid systems and rural electrification, which are frequently optimized using metaheuristic techniques.

Moreover, the total renewable energy share in national generation portfolios influences modelling complexity. Countries with high renewable penetration require detailed temporal modeling and flexibility analysis, while low-penetration systems may prioritize expansion planning and cost minimization.

Role of Economic Incentives in Shaping Optimization Models

Economic policy instruments such as feed-in tariffs, carbon pricing, renewable portfolio standards, and investment subsidies significantly affect model formulation and optimization objectives. In countries with carbon pricing mechanisms, objective functions often incorporate emission cost terms, leading to stronger renewable penetration in optimal solutions. Conversely, in subsidy-driven systems, investment constraints and payback period considerations become dominant modelling parameters. Therefore, optimization models are not purely technical constructs but reflect the policy and economic landscape in which they are applied.

Open-Source Modeling Frameworks: OEMOFs and Alternatives

Open-source frameworks have become essential tools for energy system analysis and planning. Several reviews have also summarized the fundamental concepts of energy system models, offering useful classifications that clarify their scope, structure, and applicability [14]. Among the most widely used frameworks are OEMOF, PyPSA, and Calliope, each providing different advantages for system representation and scenario analysis. In addition, OSeMOSYS has also been the subject of a recent systematic review that highlights its diverse applications, continuous developments, and potential future research directions [86]. Beyond system-wide applications, open-source approaches have also been extended to sector-specific domains. For instance, Ball et al. [87] introduced an open-source framework for large-scale building energy modelling, enabling transparent and scalable analysis of building-level performance.

OEMOF is a Python-based platform that builds flexible and modular energy system models [11]. Its main advantages are its ability to accommodate different energy sources and sectors (electricity, heat, transportation) and support for multi-node and multi-commodity modeling.

OEMOF uses a graph-based approach and can be adapted to solvers such as CBC, CPLEX, or Gurobi, especially in MILP-based optimization.

In a study by [88], OEMOF was used in Germany, particularly by the University of Applied Sciences Nordhausen, to model the energy system of the state of Thuringia to achieve the goal of carbon neutrality by 2050. The model covers the electricity, heat, and mobility sectors with hourly time resolution and integrates various technologies such as renewable energy, Power-to-X, and energy storage. The results are used to evaluate the most efficient and low-emission energy transition pathways, making OEMOF an effective tool for open data-driven energy policy analysis at the regional level.

Beyond this example, OEMOF has been increasingly adopted across Western Europe, especially in countries with firm commitments to open science and decarbonization policies. Germany, where OEMOF originated, provides an ecosystem that fosters the development of open-source energy tools—through academic collaboration, national energy transition goals, and a culture of transparent data sharing. These factors have positioned OEMOF as a widely accepted modeling framework in research and institutional planning contexts. This reflects a broader trend in the modelling community, where open-source tools are increasingly leveraged to enhance transparency, reproducibility, and collaborative research, as highlighted by DeCarolis *et al.* [89].

PyPSA (Python for Power System Analysis)

PyPSA (Python for Power System Analysis) is an open-source framework for modeling and optimizing energy systems across the electricity, heat, transportation, and hydrogen sectors. With high spatial and temporal resolution, PyPSA enables modular simulation from local to regional scales. It supports power flow analysis, capacity expansion, and system cost optimization, making it a flexible and inclusive solution for open-data-driven energy transition planning [90].

PyPSA excels in large-scale energy system modeling and integrated power grids with high mathematical optimization capabilities. It is suitable for long-term analysis and national or regional policy studies. Meanwhile, OEMOF is more architecturally flexible and robust for simulations of complex and modular local energy systems, especially for community-based studies or energy decentralization projects. The choice between the two depends on the system's scale, the study's purpose, and the need for technical analysis.

From a structural perspective, OEMOF's graph-based modular architecture allows explicit representation of multi-commodity flows (electricity, heat, gas, hydrogen) within a unified object-oriented framework. This provides flexibility in modelling decentralized regional systems where sector coupling is essential.

PyPSA, on the other hand, demonstrates superior performance in large-scale transmission grid modeling due to its optimized linear power flow implementation. However, quantitative benchmarking studies directly comparing runtime or scalability between OEMOF and PyPSA for multi-commodity regional systems remain limited in the literature. Thus, while OEMOF offers architectural transparency and cross-sector modular flexibility, the measurable advantage depends on modelling objectives, spatial scale, and solver configuration.

Calliope

Calliope is an open-source energy systems modeling framework that adopts a declarative approach [91], making it easier for users to compile models with a simpler syntax than OEMOF or PyPSA. Calliope is ideal for energy system modeling in the context of location and capacity optimization and simulating the trade-off between costs and emissions.

The advantages of the Calliope framework lie in its ease of use by non-programmer users and the excellent documentation. However, the limitation is in structural flexibility and scalability for large models with multiple nodes or technologies. Key technical aspects,

including modeling scale, sectoral focus, and ease of use, are compared across OEMOF, PyPSA, and Calliope in **Table 3**.

Table 3. Technical comparison between OEMOF, Pypsa, and Calliope

Key Feature	OEMOF	PyPSA	Calliope
Programming Language	Python	Python	Python
Modeling Architecture	Modular, graph-based structure	Network-based power system modeling	Declarative, YAML-based configuration
Optimization Approach	LP/MILP (flexible solver integration: CBC, CPLEX, Gurobi)	Linear optimal power flow (LOPF), MILP, AC-OPF	LP/MILP
Primary Sector Focus	Multi-sector (electricity, heat, transport, gas, hydrogen)	Primarily electricity systems (with sector-coupling extensions)	Flexible depending on the user-defined scope
Modeling Scale	Local, regional, national	National, continental (e.g., European grid studies)	Local to national
Ease of Use	Medium (requires Python familiarity)	Medium–High (strong documentation for power system users)	High (user-friendly syntax for beginners)
Scalability	High for modular multi-commodity systems	Very high for large-scale transmission modeling	Moderate for large multi-node systems
Community & Documentation	Active academic community	Very active international community	Active but smaller user base

The choice of framework depends mainly on the study's objectives, the sector's scope, and the user's level of expertise. OEMOF is suitable for cross-sectoral national energy modeling with flexible scenario needs. PyPSA is ideal for large-scale electricity simulations and cross-border interconnections, while Calliope offers an efficient starting point for trade-off-based energy system analysis at the local or national level.

Thematic Discussions: Advantages, Limitations, and Implications

Deterministic methods such as LP and MILP offer advantages in accuracy, transparency, and the ability to generate optimal solutions in well-defined systems. Its reliability makes it a top choice in long-term policy-based studies, especially in developed countries with well-established data and computing infrastructure.

Meanwhile, metaheuristic algorithms demonstrate high flexibility for complex and nonlinear energy systems and provide competitive solutions for realistic energy system configurations in developing countries. This approach is especially beneficial in regions with limited data or technical resources.

Artificial intelligence (AI)-based approaches offer strong adaptivity to dynamically changing conditions, such as weather fluctuations or energy demand. AI also strengthens the potential for integrating IoT-based systems and smart grids, making it particularly relevant for future energy planning scenarios.

Open-source frameworks such as OEMOF, PyPSA, and Calliope contribute to model development's transparency, flexibility, and sustainability. The existence of an active community and good documentation also strengthens the position of this framework in supporting evidence-based energy planning systems. In this context, OSeMOSYS Global has also emerged as a notable initiative, demonstrating how open-source and open-data modelling can be applied to generate large-scale electricity system models with high transparency and

global comparability [96]. OEMOF, in particular, shows practical advantages in countries like Germany, where policy support, academic collaboration, and open data culture accelerate its real-world adoption in national energy planning.

Some of the key limitations found include:

1. The reliance of AI models on quality and adequate training data.
2. The complexity of calculations in MILP is high when the scale of the model is large and involves many integer variables.
3. Low interpretability on AI-based models (black-box problem).
4. Most studies have weak integration between technical and socio-economic dimensions, especially in developing countries. Recent reviews also highlight that multi-criteria decision-making (MCDM) approaches provide a structured way to incorporate sustainability, environmental, and social considerations into decentralized hybrid energy systems, helping to overcome this limitation [97].
5. There is no standard for the evaluation or benchmarking of models between countries. According to a recent comprehensive review, although MCDM methods have advanced significantly and are increasingly applied in renewable energy systems, they still face challenges related to standardization, comparability, and consistent evaluation frameworks across studies [98].

In addition, although open-source frameworks are growing in popularity, their adoption rates in developing countries are still low due to a lack of human resources, technical training, and policy support. To address these gaps, recent studies recommend integrating multi-criteria decision making (MCDM) frameworks into hybrid renewable energy system design, allowing for a more systematic balance between technical, economic, environmental, and social objectives [99].

Policy Implications and Future Research Directions

This study shows that the optimization approach in national energy planning must be adapted to the local technical, socio-economic, and policy context. Hybrid methods—which combine deterministic, metaheuristic, and AI—are a strategic direction to address the challenges of dynamic future energy systems.

From a policy perspective, it is necessary to:

1. Strengthen technical capacity in developing countries,
2. Cross-border collaborative approach to open-source technology transfer such as OEMOF,
3. And the development of an open and standardized national energy data ecosystem.

From the research side, there is a need for encouragement to integrate socio-economic aspects into optimization models, as well as the development of visual and interactive tools that strengthen the role of models as decision-support tools in long-term energy planning.

CONCLUSION

This systematic literature review examined 54 studies to classify optimization methods and open-source frameworks used in national renewable energy planning. A key finding of this study is that deterministic approaches such as LP and MILP are predominantly used in developed countries, where energy systems are more stable and structured. In contrast, developing countries tend to rely more on metaheuristic algorithms such as GA, PSO, and GWO, which are better suited to handle data limitations and complex system conditions. Additionally, AI-based methods such as ANN and LSTM are gaining traction for dynamic modeling and prediction, although they require large training datasets.

Open-source frameworks such as OEMOF, PyPSA, and Calliope play a crucial role in promoting transparent, replicable, and adaptable energy planning processes. The study also highlights a significant contrast in methodological orientation between developed and developing countries—with the former focusing on cross-sectoral integration and policy scenario analysis, while the latter prioritize expanding energy access and cost efficiency.

Since no single method proves universally superior, recent reviews also emphasize that the optimization of hybrid energy systems requires balancing accuracy, robustness, and computational efficiency across diverse methods [100]. Developing hybrid approaches that combine the strengths of deterministic, metaheuristic, and AI techniques emerges as a promising strategy to support resilient and sustainable national energy planning. Looking forward, future research should focus on integrating technical and socio-economic modeling, evaluating the applicability of open-source tools in developing country contexts, and creating interactive decision-support tools to enhance data-driven policymaking.

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Symbols and abbreviations

LCOE	Levelized Cost of Energy [EUR/kWh]
AI	Artificial Intelligence
ANN	Artificial Neural Network
BESS	Battery-based Energy Storage System
DH	District Heating
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
IoT	Internet of Things
LP	Linear Programming
LSTM	Long Short-Term Memory
MILP	Mixed-Integer Linear Programming
OEMOF	Open Energy Modelling Framework
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimization
PyPSA	Python for Power System Analysis
SSP	Social Spider Prey Algorithm
SVM	Support Vector Machine

REFERENCES

1. S. L. Samarasinghe, M. Moghimi, and P. Kaparaju, “A review of modelling tools for net-zero emission energy systems, based on model capabilities, modelling criteria and model availability,” *Renew. Energy Focus*, Vol. 53, No. November 2024, Art. no. 100659, 2025, <https://doi.org/10.1016/j.ref.2024.100659>.

2. L. Juarez-Rojas, A. Alvarez-Risco, N. Campos-Dávalos, M. de las Mercedes Anderson-Seminario, and S. Del-Aguila-Arcentales, “Effectiveness of Renewable Energy Policies in Promoting Green Entrepreneurship: A Global Benchmark Comparison”, In: A. Alvarez-Risco, S.S. Muthu, and S. Del-Aguila-Arcentales (Eds), *Footprint and Entrepreneurship. Environmental Footprints and Eco-design of Products and Processes*. Springer, Singapore, 2023, pp. 47–87, https://doi.org/10.1007/978-981-19-8895-0_3.
3. N. Y. M. Yusoff, H. Aris, W. H. M. Nasiruddin, A. K. C. Rusli, Z. Yurnaidi, R. Safrina, N. A. Utama, and S. A. Rosalia, “The driving forces behind renewable energy consumption: A comprehensive analysis of key determinants and environmental concerns in ASEAN countries,” *Environ. Sci. Pollut. Res.*, Vol. 31, No. 35, pp. 48388–48405, 2024, <https://doi.org/10.1007/s11356-024-34358-8>.
4. M. M. Mundu, S. N. Nnamchi, J. I. Sempewo, and D. E. Uti, “Simulation modeling for energy systems analysis: a critical review,” *Energy Informatics*, Vol. 7, No. 1, Art. no. 75, 2024, <https://doi.org/10.1186/s42162-024-00374-8>.
5. M. Tangi and A. Amaranto, “Advancements in Multi-Objective Optimization for Planning and Management of Multi-Energy Systems,” *J. Sustain. Dev. Energy, Water Environ. Syst.*, Vol. 13, No. 2, pp. 1–21, 2025, <https://doi.org/10.13044/j.sdewes.d13.0584>.
6. G. Parrado-Hernando, F. Frechoso-Escudero, and L. J. Miguel González, “Method to Model the Hourly Variability of Renewable Energy Sources in Integrated Assessment Models,” *J. Sustain. Dev. Energy, Water Environ. Syst.*, Vol. 12, No. 1, Art. no. 1110481, 2024, <https://doi.org/10.13044/J.SDEWES.D11.0481>.
7. D. Díaz-Bello, C. Vargas-Salgado, J. Águila-León, and D. Alfonso-Solar, “Smart Energy Management for Hybrid Systems: A Genetic Algorithm in Response to Market Volatility,” *J. Sustain. Dev. Energy, Water Environ. Syst.*, Vol. 13, No. 2, Art. no. 1130536, 2025, <https://doi.org/10.13044/j.sdewes.d13.0536>.
8. M. Thirunavukkarasu, Y. Sawle, and H. Lala, “A comprehensive review on optimization of hybrid renewable energy systems using various optimization techniques,” *Renew. Sustain. Energy Rev.*, Vol. 176, Art. no. 113192, 2023, <https://doi.org/10.1016/j.rser.2023.113192>.
9. A. S. Menesy, H. M. Sultan, I. O. Habiballah, H. Masrur, K. R. Khan, and M. Khalid, “Optimal Configuration of a Hybrid Photovoltaic/Wind Turbine/Biomass/Hydro-Pumped Storage-Based Energy System Using a Heap-Based Optimization Algorithm,” *Energies*, Vol. 16, Art. no. 3648, 2023, <https://doi.org/https://doi.org/10.3390/en16093648>.
10. S. Hilpert, S. Günther, C. Kaldemeyer, U. Krien, G. Plessmann, F. Wiese, and C. Wingenbach, “Addressing Energy System Modelling Challenges: The Contribution of the Open Energy Modelling Framework (OEMOF),” 2017. <https://doi.org/10.20944/preprints201702.0055.v1>.
11. S. Hilpert, C. Kaldemeyer, U. Krien, S. Günther, C. Wingenbach, and G. Plessmann, “The Open Energy Modelling Framework (OEMOF) - a new approach to facilitate open science in energy system modelling,” *Energy Strateg. Rev.*, Vol. 22, No. July, pp. 16–25, 2018, <https://doi.org/10.1016/j.esr.2018.07.001>.
12. S. Yu, L. You, and S. Zhou, “A review of optimization modeling and solution methods in renewable energy systems,” *Front. Eng. Manag.*, Vol. 10, No. 4, pp. 640–671, 2023, <https://doi.org/10.1007/s42524-023-0271-3>.
13. A. Giedraityte, S. Rimkevicius, M. Marciukaitis, V. Radziukynas, and R. Bakas, “Hybrid Renewable Energy Systems—A Review of Optimization Approaches and Future Challenges,” *Appl. Sci.*, Vol. 15, No. 4, Art. no. 1744, 2025, <https://doi.org/10.3390/app15041744>.
14. P. Bendigiri and P. Rao, “Energy system models: a review of concepts and recent advances using bibliometrics,” *Int. J. Sustain. Energy*, Vol. 42, No. 1, pp. 975–1007, 2023, <https://doi.org/10.1080/14786451.2023.2246082>.
15. M. F. R. H. Rambey, E. A. Setiawan, and A. F. Madsuha, “PV industry in China and three Southeast Asia countries: A systematic literature review using PRISMA,” *IOP Conf. Ser. Earth Environ. Sci.*, Vol. 997, Art. no. 012021, 2022, <https://doi.org/10.1088/1755-1315/997/1/012021>.

- 16.S. Eslami, Y. Noorollahi, M. Marzband, and A. Anvari-Moghaddam, "Integrating heat pumps into district heating systems: A multi-criteria decision analysis framework incorporating heat density and renewable energy mapping," *Sustain. Cities Soc.*, Vol. 98, Art. no. 104785, 2023, <https://doi.org/10.1016/j.scs.2023.104785>.
- 17.E. Rakhshani, H. Mehrjerdi, and A. Iqbal, "Hybrid wind-diesel-battery system planning considering multiple different wind turbine technologies installation," *J. Clean. Prod.*, Vol. 247, Art. no. 119654, 2020, <https://doi.org/10.1016/j.jclepro.2019.119654>.
- 18.J. Zhang and H. Wei, "A review on configuration optimization of hybrid energy system based on renewable energy," *Front. Energy Res.*, Vol. 10, no. August, Art. no. 977925, 2022, <https://doi.org/10.3389/fenrg.2022.977925>.
- 19.O. Bamisile, D. Cai, H. Adun, M. Dagbasi, C. C. Ukwuoma, Q. Huang, N. Johnson, and O. Bamisile, "Towards renewables development: Review of optimization techniques for energy storage and hybrid renewable energy systems," *Heliyon*, Vol. 10, No. 19, Art. no. e37482, 2024, <https://doi.org/10.1016/j.heliyon.2024.e37482>.
- 20.Q. Hassan, S. Algburi, A. Z. Sameen, H. M. Salman, and M. Jaszczur, "A review of hybrid renewable energy systems: Solar and wind-powered solutions: Challenges, opportunities, and policy implications," *Results in Engineering*, Vol. 20, Art. no. 101621, 2023, <https://doi.org/10.1016/j.rineng.2023.101621>.
- 21.O. K. Ajiboye, C. V. Ochiegbu, E. A. Ofosu, and S. Gyamfi, "A review of hybrid renewable energies optimisation: design, methodologies, and criteria," *Int. J. Sustain. Energy*, Vol. 42, No. 1, pp. 648–684, 2023, <https://doi.org/10.1080/14786451.2023.2227294>.
- 22.F. Peterssen, M. Schlemminger, C. Lohr, R. Niepelt, R. Hanke-Rauschenbach, and R. Brendel, "Impact of forecasting on energy system optimization," *Adv. Appl. Energy*, Vol. 15, Art. no. 100181, 2024, <https://doi.org/10.1016/j.adapen.2024.100181>.
- 23.J. Lujano-Rojas, R. Dufo-López, and J. A. Domínguez-Navarro, "Optimization of renewable energy systems by genetic algorithms," In: *Genetic Optimization Techniques for Sizing and Management of Modern Power Systems*, Elsevier, Oxford, United Kingdom, 2023, pp. 247–281, <https://doi.org/10.1016/B978-0-12-823889-9.00007-2>.
- 24.Z. Hu, C. Dai, and Q. Su, "Adaptive backtracking search optimization algorithm with a dual-learning strategy for dynamic economic dispatch with valve-point effects," *Energy*, Vol. 248, Art. no. 123558, 2022, <https://doi.org/10.1016/j.energy.2022.123558>.
- 25.K. Ullah, G. Hafeez, I. Khan, S. Jan, and N. Javaid, "A multi-objective energy optimization in smart grid with high penetration of renewable energy sources," *Appl. Energy*, Vol. 299, Art. no. 117104, 2021, <https://doi.org/10.1016/j.apenergy.2021.117104>.
- 26.S. Hasan, A. Islam Meem, M. Saiful Islam, S. Sabrina Proma, and S. Kumar Mitra, "Comparative techno-economic analyses and optimization of standalone and grid-tied renewable energy systems for South Asia and Sub-Saharan Africa," *Results Eng.*, Vol. 21, Art. no. 101964, 2024, <https://doi.org/10.1016/j.rineng.2024.101964>.
- 27.A. Mathur, R. Kumari, V. P. Meena, V. P. Singh, A. T. Azar, and I. A. Hameed, "Data-driven optimization for microgrid control under distributed energy resource variability," *Scientific Reports*, Vol. 14, Art. no. 10806, 2024, <https://doi.org/10.1038/s41598-024-58767-4>.
- 28.C. K. Rao, S. K. Sahoo, and F. F. Yanine, "IoT enabled Intelligent Energy Management System employing advanced forecasting algorithms and load optimization strategies to enhance renewable energy generation," *Unconv. Resour.*, Vol. 4, Art. no. 100101, 2024, <https://doi.org/10.1016/j.unres.2024.100101>.
- 29.A. U. Rehman, Z. Wadud, R. M. Elavarasan, G. Hafeez, I. Khan, Z. Shafiq, and H. H. Alhelou, "An Optimal Power Usage Scheduling in Smart Grid Integrated with Renewable Energy Sources for Energy Management," *IEEE Access*, Vol. 9, pp. 84619–84638, 2021, <https://doi.org/10.1109/ACCESS.2021.3087321>.
- 30.B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili, "African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems," *Comput. Ind. Eng.*, Vol. 158, Art. no. 107408, 2021, <https://doi.org/10.1016/j.cie.2021.107408>.

31. S. O. Frimpong, "Optimization of hybrid renewable energy generation using a nature-inspired algorithm with advanced IoT analytics," PhD Thesis, Durban University of Technology, Durban, South Africa, 2022, <https://openscholar.dut.ac.za/items/2c5f9526-7690-4a12-bf4e-36fbbfbbb880>, [Accessed: 09-March-2026].
32. Y. He, S. Guo, P. Dong, Y. Zhang, J. Huang, and J. Zhou, "A state-of-the-art review and bibliometric analysis on the sizing optimization of off-grid hybrid renewable energy systems," *Renew. Sustain. Energy Rev.*, Vol. 183, Art. no. 113476, 2023, <https://doi.org/10.1016/j.rser.2023.113476>.
33. U. Lakhina, N. Badruddin, I. Elamvazuthi, A. Jangra, T. H. B. Huy, and J. M. Guerrero, "An Enhanced Multi-Objective Optimizer for Stochastic Generation Optimization in Islanded Renewable Energy Microgrids," *Mathematics*, Vol. 11, No. 9, Art. no. 2079, 2023, <https://doi.org/10.3390/math11092079>.
34. S. Moghaddam, M. Bigdeli, and M. Moradlou, "Optimal design of an off-grid hybrid renewable energy system considering generation and load uncertainty: the case of Zanzan city, Iran," *SN Appl. Sci.*, Vol. 3, No. 8, Art. no.732, 2021, <https://doi.org/10.1007/s42452-021-04718-x>.
35. L. E. Natividad and P. Benalcazar, "Hybrid Renewable Energy Systems for Sustainable Rural Development : Perspectives and Challenges in Energy Systems Modeling," *Energies*, Vol. 16, Art. no. 1328, 2023, <https://doi.org/https://www.doi.org/10.3390/en16031328>.
36. L. Y. Yab, N. Wahid, and R. A. Hamid, "Inversed Control Parameter in Whale Optimization Algorithm and Grey Wolf Optimizer for Wrapper-Based Feature Selection: A Comparative Study," *Int. J. Informatics Vis.*, Vol. 7, No. 2, pp. 477–486, 2023, <https://doi.org/10.30630/joiv.7.2.1509>.
37. M. M. Rahman, M. Shakeri, S. K. Tiong, F. Khatun, N. Amin, J. Pasupuleti, and M. K. Hasan, "Prospective methodologies in hybrid renewable energy systems for energy prediction using artificial neural networks," *Sustain.*, Vol. 13, No. 4, Art. no. 2393, 2021, <https://doi.org/10.3390/su13042393>.
38. A. M. Barbosa, P. Rotella Junior, L. C. S. Rocha, A. de S. Barbosa, and I. Bolis, "Optimization methods of distributed hybrid power systems with battery storage system: A systematic review," *J. Energy Storage*, Vol. 97, Art. no. 112909, 2024, <https://doi.org/10.1016/j.est.2024.112909>.
39. S. O. Frimpong, I. E. Agbehadji, A. Abayomi, R. C. Millham, E. Freeman, and M. M. Ujakpa, "Economic and reliability determination of sustainable renewable energy mix based on social spider prey optimization algorithm," *Soft Comput.*, Vol. 27, No. 15, pp. 10687–10718, 2023, <https://doi.org/10.1007/s00500-023-08231-8>.
40. M. Thirunavukkarasu, H. Lala, and Y. Sawle, "Reliability index based optimal sizing and statistical performance analysis of stand-alone hybrid renewable energy system using metaheuristic algorithms," *Alexandria Eng. J.*, Vol. 74, pp. 387–413, 2023, <https://doi.org/10.1016/j.aej.2023.04.070>.
41. H. M. Abdullah, S. Park, K. Seong, and S. Lee, "Hybrid Renewable Energy System Design: A Machine Learning Approach for Optimal Sizing with Net-Metering Costs," *Sustain.*, Vol. 15, No. 11, Art. no. 8538, 2023, <https://doi.org/10.3390/su15118538>.
42. A. M. Iung, F. L. Cyrino Oliveira, and A. L. M. Marcato, "A Review on Modeling Variable Renewable Energy: Complementarity and Spatial–Temporal Dependence," *Energies*, Vol. 16, No. 3, Art. no. 1013, 2023, <https://doi.org/10.3390/en16031013>.
43. M. Mahmood, P. Chowdhury, R. Yeassin, M. Hasan, T. Ahmad, and N. U. R. Chowdhury, "Impacts of digitalization on smart grids, renewable energy, and demand response: An updated review of current applications," *Energy Convers. Manag. X*, Vol. 24, Art. no. 100790, 2024, <https://doi.org/10.1016/j.ecmx.2024.100790>.
44. F. Yao, W. Zhou, M. Al Ghamdi, Y. Song, and W. Zhao, "An integrated D-CNN-LSTM approach for short-term heat demand prediction in district heating systems," *Energy Reports*, Vol. 8, pp. 98–107, 2022, <https://doi.org/10.1016/j.egypr.2022.08.087>.

- 45.W. Bensalmi, A. Belhani, and A. Bouzid-Daho, "Exploring Advanced Methodologies for Hybrid Energy System Sizing through Artificial Intelligence Techniques: a comprehensive review," *J. Renew. Energies*, Vol. 2024, pp. 85–100, 2024, <https://doi.org/10.54966/jreen.v1i1.1296>.
- 46.L. C. P. Velasco, D. L. L. Polestico, D. M. M. Abella, G. T. Alegata, and G. C. Luna, "Performance Analysis of Support Vector Regression Machine Models in Day-Ahead Load Forecasting", In: K. Arai, S. Kapoor, R. Bhatia (Eds) *Advances in Information and Communication. FICC 2020. Advances in Intelligent Systems and Computing*, Vol. 1130, pp. 541–555, Springer, Cham, Switzerland. https://doi.org/10.1007/978-3-030-39442-4_40 2020.
- 47.G. Vonitsanos, A. Kanavos, and P. Mylonas, "Evaluating Machine Learning Techniques for Enhanced Prediction of Building Energy Consumption," In: 2024 9th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM), Sep. 2024, pp. 50–57, <https://doi.org/10.1109/SEEDA-CECNSM63478.2024.00018>.
- 48.T. Lees, M. Buechel, B. Anderson, L. Slater, S. Reece, G. Coxon, and S. J. Dadson, "Benchmarking data-driven rainfall-runoff models in Great Britain: A comparison of long short-term memory (LSTM)-based models with four lumped conceptual models," *Hydrol. Earth Syst. Sci.*, Vol. 25, No. 10, pp. 5517–5534, 2021, <https://doi.org/10.5194/hess-25-5517-2021>.
- 49.L. Laveneziana, M. Prussi, and D. Chiamonti, "Critical review of energy planning models for the sustainable development at company level," *Energy Strateg. Rev.*, Vol. 49, Art. no. 101136, 2023, <https://doi.org/10.1016/j.esr.2023.101136>.
- 50.H. I. Yilmaz and Y. Gonbe, "Modeling favorable locations for biogas plants that generate electricity from dairy and beef cattle manure through mixed integer linear programming," *BioResources*, Vol. 19, No. 3, pp. 4517–4530, 2024, <https://doi.org/10.15376/biores.19.3.4517-4530>.
- 51.A. S. Ansari, T. Hussain, A. Hussain, and I. Ali, "Efficiency Analysis of Archimedes Wind Turbine Using CFD Technique," *Int. J. Sci. Eng. Res.*, Vol. 12, No. 3, pp. 51–55, 2021, https://www.researchgate.net/profile/Arshad-Jamali/publication/351771320_Efficiency_Analysis_of_Archimedes_Wind_Turbine_Using_CFD_Technique/links/60a88f26a6fdcc6d62664a43/Efficiency-Analysis-of-Archimedes-Wind-Turbine-Using-CFD-Technique.pdf?tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19, [Accessed: 09-March-2026].
- 52.A. Guasque and P. Balbastre, "Evaluation and Comparison of Integer Programming Solvers for Hard Real-Time Scheduling," *IEICE Trans. Inf. Syst.*, Vol. E105D, No. 10, pp. 1726–1733, 2022, <https://doi.org/10.1587/transinf.2022EDP7073>.
- 53.P. G. Saghand and H. Charkhgard, "Exact solution approaches for integer linear generalized maximum multiplicative programs through the lens of multi-objective optimization," *Comput. Oper. Res.*, Vol. 137, Art. no. 105549, 2022, <https://doi.org/10.1016/j.cor.2021.105549>.
- 54.X. Zhang, S. Zhang, S. Liu, Y. Wang, B. Yang, Y. Wang, and T. Ding, "A Hybrid Stochastic/Robust Planning Model for Integrated Energy System Considering Multiple Uncertainties," *Appl. Math. Nonlinear Sci.*, Vol. 9, No. 1, pp. 1–22, 2023, <https://doi.org/10.2478/amns.2023.1.00147>.
- 55.R. Ahmed, V. Sreeram, Y. Mishra, and M. D. Arif, "A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization," *Renew. Sustain. Energy Rev.*, Vol. 124, Art. no. 109792, 2020, <https://doi.org/10.1016/j.rser.2020.109792>.
- 56.A. A. Hassan and K. El-Rayes, "Optimizing the integration of renewable energy in existing buildings," *Energy Build.*, Vol. 238, 2021, <https://doi.org/10.1016/j.enbuild.2021.110851>.
- 57.R. Mouachi, M. A. Jallal, F. Gharnati, and M. Raoufi, "Multiobjective Sizing of an Autonomous Hybrid Microgrid Using a Multimodal Delayed PSO Algorithm: A Case Study

- of a Fishing Village,” *Comput. Intell. Neurosci.*, Vol. 2020, pp. 1–18, 2020, <https://doi.org/10.1155/2020/8894094>.
- 58.C. Krishna Rao, S. K. Sahoo, and F. F. Yanine, “IoT enabled Intelligent Energy Management System employing advanced forecasting algorithms and load optimization strategies to enhance renewable energy generation,” *Unconv. Resour.*, Vol. 4, Art. no. 100101, 2024, <https://doi.org/10.1016/j.uncred.2024.100101>.
- 59.M. Mohammadian, A. Lorestani, and M. M. Ardehali, “Optimization of single and multi-areas economic dispatch problems based on evolutionary particle swarm optimization algorithm,” *Energy*, Vol. 161, pp. 710–724, 2018, <https://doi.org/10.1016/j.energy.2018.07.167>.
- 60.R. Mukesh, R. Pandiyarajan, U. Selvakumar, and K. Lingadurai, “Influence of search algorithms on aerodynamic design optimisation of aircraft wings,” *Procedia Eng.*, Vol. 38, pp. 2155–2163, 2012, <https://doi.org/10.1016/j.proeng.2012.06.259>.
- 61.F. Liu, Y. Mu, and Z. Chen, “Control Strategy for Improving the Voltage Regulation Ability of Low-Carbon Energy Systems with High Proportion of Renewable Energy Integration,” *Electron.*, Vol. 12, No. 11, Art. no. 2513 2023, <https://doi.org/10.3390/electronics12112513>.
- 62.Z. Qadir, S. I. Khan, E. Khalaji, H. S. Munawar, F. Al-Turjman, M. A. P. Mahmud, A. Z. Kouzani, and K. Le, “Predicting the energy output of hybrid PV–wind renewable energy system using feature selection technique for smart grids,” *Energy Reports*, Vol. 7, pp. 8465–8475, 2021, <https://doi.org/10.1016/j.egy.2021.01.018>.
- 63.M. Abdelsattar, M. A. Ismeil, K. Menoufi, A. AbdelMoety, and A. Emad-Eldeen, “Evaluating Machine Learning and Deep Learning models for predicting Wind Turbine power output from environmental factors,” *PLoS One*, Vol. 20, No. 1, Art. no. e0317619, 2025, <https://doi.org/10.1371/journal.pone.0317619>.
- 64.M. W. Hasan, “Design of an IoT model for forecasting energy consumption of residential buildings based on improved long short-term memory (LSTM),” *Meas. Energy*, Vol. 5, Art. no. 100033, 2025, <https://doi.org/10.1016/j.meae.2024.100033>.
- 65.C. Roberts and F. W. Geels, “Conditions and intervention strategies for the deliberate acceleration of socio-technical transitions: lessons from a comparative multi-level analysis of two historical case studies in Dutch and Danish heating,” *Technol. Anal. Strateg. Manag.*, Vol. 31, No. 9, pp. 1081–1103, 2019, <https://doi.org/10.1080/09537325.2019.1584286>.
- 66.N. K. Siavash, B. Ghobadian, G. Najafi, A. Rohani, T. Tavakoli, E. Mahmoodi, R. Mamat, and M. mazlan, “Prediction of power generation and rotor angular speed of a small wind turbine equipped to a controllable duct using artificial neural network and multiple linear regression,” *Environ. Res.*, Vol. 196, Art. no. 110434, 2021, <https://doi.org/10.1016/j.envres.2020.110434>.
- 67.J. Sargolzaei, “Prediction of the power ratio in wind turbine Savonius rotors using artificial neural networks,” *International Journal of Energy and Environment*, Vol. 1, No. 2, pp. 51–55, 2007, <https://www.naun.org/main/NAUN/energyenvironment/ee-09.pdf>, [Accessed: 09-March-2026]
- 68.R. Kumar and S. K. Mishra, “Operational reliability evaluation integrating prediction models for enhanced situational awareness in wind-integrated system,” *Comput. Electr. Eng.*, Vol. 118, Art. no. 109454, 2024, <https://doi.org/10.1016/j.compeleceng.2024.109454>.
- 69.E. M. Veith, *Universal Smart Grid Agent for Distributed Power Generation Management*. Logos Verlag Berlin, Germany, 2017, <https://doi.org/10.30819/4512>.
- 70.K. Saini, M. Saini, A. Kumar, and D. K. Saini, “Performance analysis and optimization in renewable energy systems: a bibliometric review,” *Discov. Appl. Sci.*, Vol. 7, No. 3, Art. no. 178, 2025, <https://doi.org/10.1007/s42452-025-06585-2>.
- 71.S. Hilpert, C. Kaldemeyer, U. Krien, S. Günther, C. Wingenbach, and G. Plessmann, “The Open Energy Modelling Framework (oemof) - A novel approach in energy system modelling,” *Energy Strateg. Rev.*, Vol. 22, pp. 16–25, 2018, <https://doi.org/10.1016/j.esr.2018.07.001>.
- 72.S. Ni, G. Brockmann, A. Darbandi, K. Shawky, and M. Kriegel, “Modelling and Optimization of a Decarbonized Heat Supply in Suburban Areas Using the Open Energy Modelling Framework,” In: 37th International Conference on Efficiency, Cost, Optimization, Simulation

- and Environmental Impact of Energy Systems (ECOS 2024), 2024, pp. 2230–2239, <https://doi.org/10.52202/077185-0191>.
- 73.P. P. Kumar, R. S. S. Nuvvula, M. A. Hossain, S. K. A. Shezan, V. Suresh, M. Jasinski, R. Gono, and Z. Leonowicz, “Optimal Operation of an Integrated Hybrid Renewable Energy System with Demand-Side Management in a Rural Context,” *Energies*, Vol. 15, No. 14, Art. no. 5176, 2022, <https://doi.org/10.3390/en15145176>.
- 74.P. R. Mishra and C. H. K. Kumar, “Real and Simulated Performance Assessment and Tilt Optimization of 5 MW Solar PV Plant Operating Under Tropical Climate of an Indian Island,” *Strateg. Plan. Energy Environ.*, pp. 1007–1028, 2024, <https://doi.org/10.13052/spee1048-5236.43410>.
- 75.S. Nirmal and T. Rizvi, “A Review of Renewable Energy Systems for Industrial Applications,” *Int. J. Res. Appl. Sci. Eng. Technol.*, Vol. 10, No. 9, pp. 2321–9653, 2022, <https://doi.org/10.22214/ijraset.2022.46903>.
- 76.S. R. Naqvi, “Recent Developments on Biomass Utilization for Bioenergy Production in Pakistan,” *Sci. Proc. Ser.*, Vol. 2, No. 2, pp. 156–160, 2020, <https://doi.org/10.31580/sps.v2i2.1461>.
- 77.M. U. Saleem, M. R. Usman, and M. Shakir, “Design, Implementation, and Deployment of an IoT Based Smart Energy Management System,” *IEEE Access*, Vol. 9, pp. 59649–59664, 2021, <https://doi.org/10.1109/ACCESS.2021.3070960>.
- 78.M. H. Jahangir, S. A. Mousavi, and R. A. Zarchi, “Implementing single- and multi-year sensitivity analyses to propose several feasible solutions for meeting the electricity demand in large-scale tourism sectors applying renewable systems,” *Environ. Dev. Sustain.*, Vol. 23, No. 10, pp. 14494–14527, 2021, <https://doi.org/10.1007/s10668-021-01254-x>.
- 79.M. Jahangiri, F. Raeiszadeh, R. Alayi, A. Najafi, and A. Tahmasebi, “Development of Rural Tourism in Iran Using PV-Based System: Finding the Best Economic Configuration,” *J. Renew. Energy Environ.*, Vol. 9, No. 4, pp. 1–9, 2022, <https://doi.org/10.30501/jree.2022.298089.1234>.
- 80.M. A. V. Rad, R. Ghasempour, P. Rahdan, S. Mousavi, and M. Arastounia, “Techno-economic analysis of a hybrid power system based on the cost-effective hydrogen production method for rural electrification, a case study in Iran,” *Energy*, Vol. 190, Art. no. 116421, 2020, <https://doi.org/10.1016/j.energy.2019.116421>.
- 81.C. Arndt, F. Hartley, G. Ireland, K. Mahrt, B. Merven, and J. Wright, “Developments in Variable Renewable Energy and Implications for Developing Countries,” *Curr. Sustain. Energy Reports*, Vol. 5, No. 4, pp. 240–246, 2018, <https://doi.org/10.1007/s40518-018-0121-9>.
- 82.I. Hoeck, E. Steurer, Ö. Dolunay, and H. Ilekka, “Challenges for off-grid electrification in rural areas. Assessment of the situation in Namibia using the examples of Gam and Tsumkwe,” *Energy, Ecol. Environ.*, Vol. 7, No. 5, pp. 508–522, 2022, <https://doi.org/10.1007/s40974-021-00214-5>.
- 83.N. J. Williams, P. Jaramillo, J. Taneja, and T. S. Ustun, “Enabling private sector investment in microgrid-based rural electrification in developing countries: A review,” *Renew. Sustain. Energy Rev.*, Vol. 52, pp. 1268–1281, 2015, <https://doi.org/10.1016/j.rser.2015.07.153>.
- 84.S. Chakraborty, D. Mukherjee, P. K. Guchhait, and S. Bhattacharjee, “Optimum Design of a Renewable-Based Integrated Energy System in Autonomous Mode for a Remote Hilly Location in,” *Energies*, Vol. 15, Art. no. 1588, 2023, <https://doi.org/https://doi.org/10.3390/en16041588>.
- 85.M. Shahzad, A. Qadir, N. Ullah, Z. Mahmood, N. M. Saad, and S. S. A. Ali, “Optimization of On-Grid Hybrid Renewable Energy System: A Case Study on Azad Jammu and Kashmir,” *Sustain.*, Vol. 14, No. 10, Art. no. 5757, 2022, <https://doi.org/10.3390/su14105757>.
- 86.F. Plazas-Niño, N. Tan, M. Howells, V. Foster, and J. Quirós-Tortós, “Uncovering the applications, developments, and future research directions of the open-source energy modelling system (OSeMOSYS): A systematic literature review,” *Energy Sustain. Dev.*, Vol. 85, Art. no. 101629, 2025, <https://doi.org/10.1016/j.esd.2024.101629>.

87. B. L. Ball, N. Long, K. Fleming, C. Balbach, and P. Lopez, "An open source analysis framework for large-scale building energy modeling," *J. Build. Perform. Simul.*, Vol. 13, No. 5, pp. 487–500, 2020, <https://doi.org/10.1080/19401493.2020.1778788>.
88. A. Oberdorfer, V. Wesselak, C. Schmidt, T. Reinhardt, and L. Hofmann, "Transition Pathways Towards a Carbon-Neutral Thuringia," *Proc. - ISES Sol. World Congr. 2021*, pp. 32–41, 2021, <https://doi.org/10.18086/swc.2021.01.05>.
89. J. F. DeCarolis *et al.*, "Leveraging Open-Source Tools for Collaborative Macro-energy System Modeling Efforts," *Joule*, Vol. 4, No. 12, pp. 2523–2526, 2020, <https://doi.org/10.1016/j.joule.2020.11.002>.
90. H. Abdel-Khalek, L. Schumm, E. Jalbout, M. Parzen, C. Schauß, and D. Fioriti, "PyPSA-Earth sector-coupled: A global open-source multi-energy system model showcased for hydrogen applications in countries of the Global South," *Appl. Energy*, Vol. 383, Art. no. 125316, 2025, <https://doi.org/10.1016/j.apenergy.2025.125316>.
91. L. Bottecchia, P. Lubello, P. Zambelli, C. Carcasci, and L. Kranzl, "The potential of simulating energy systems: The multi energy systems simulator model," *Energies*, Vol. 14, No. 18, Art. no. 5724, 2021, <https://doi.org/10.3390/en14185724>.
92. H. Sitompul, M. Saifi, B. Hutahayan, and Sunarti, "Use of Renewable Energy to Enhance Firm Performance: A Systematic Review," *Sustainability*, Vol. 16, No. 21, Art. no. 9157, 2024, <https://doi.org/10.3390/su16219157>.
93. P. R. Patil, K. Dhamale, S. L. Peris, B. U. K. Reddy, and G. Dhungel, "Energy System Modelling of Denmark using OEMOF," Project Report, Hochschule Nordhausen, Thuringia, Germany, 2020. <https://doi.org/10.13140/RG.2.2.34068.86407>.
94. S. Berendes, S. Hilpert, S. Günther, C. Muschner, S. Candas, K. Hainsch, J. van Ouwerkerk, S. Buchholz, and M. Söthe, "Evaluating the usability of open source frameworks in energy system modelling," *Renew. Sustain. Energy Rev.*, Vol. 159, Art. no. 112174, 2022, <https://doi.org/10.1016/j.rser.2022.112174>.
95. S. Candas, C. Muschner, S. Buchholz, R. Bramstoft, J. van Ouwerkerk, K. Hainsch, K. Löffler, S. Günther, S. Berendes, S. Nguyen, and A. Justin, "Code exposed: Review of five open-source frameworks for modeling renewable energy systems," *Renew. Sustain. Energy Rev.*, Vol. 161, Art. no. 112272, 2022, <https://doi.org/10.1016/j.rser.2022.112272>.
96. T. Barnes, A. Shivakumar, M. Brinkerink, and T. Niet, "OSeMOSYS Global, an open-source, open data global electricity system model generator," *Sci. Data*, Vol. 9, No. 1, Art. no. 623, 2022, <https://doi.org/10.1038/s41597-022-01737-0>.
97. S. Das, R. Dutta, S. De, and S. De, "Review of multi-criteria decision-making for sustainable decentralized hybrid energy systems," *Renew. Sustain. Energy Rev.*, Vol. 202, Art. no. 114676, 2024, <https://doi.org/10.1016/j.rser.2024.114676>.
98. S. K. Sahoo and S. S. Goswami, "A Comprehensive Review of Multiple Criteria Decision-Making (MCDM) Methods: Advancements, Applications, and Future Directions," *Decis. Mak. Adv.*, Vol. 1, No. 1, pp. 25–48, 2023, <https://doi.org/10.31181/dma1120237>.
99. T. N. D. Mathaba and K. Abo-Al-Ez, "Design of Hybrid Renewable Energy Systems: Integrating Multi-Objective Optimization Into a Multi-Criteria Decision-Making Framework," *Eng. Reports*, Vol. 7, No. 1, Art. no. e13074, 2025, <https://doi.org/10.1002/eng2.13074>.
100. A. Khan, M. Bressel, A. Davigny, D. Abbes, and B. Ould Bouamama, "Comprehensive Review of Hybrid Energy Systems: Challenges, Applications, and Optimization Strategies," *Energies*, Vol. 18, No. 10, Art. no. 2612, 2025, <https://doi.org/10.3390/en18102612>.



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