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REVIEW ARTICLE

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A review of optimization modeling and solution methods in renewable energy systems

Abstract The advancement of renewable energy (RE) represents a pivotal strategy in mitigating climate change and advancing energy transition efforts. A current of research pertains to strategies for fostering RE growth. Among the frequently proposed approaches, employing optimization models to facilitate decision-making stands out prominently. Drawing from an extensive dataset comprising 32806 literature entries encompassing the optimization of renewable energy systems (RES) from 1990 to 2023 within the Web of Science database, this study reviews the decision-making optimization problems, models, and solution methods thereof throughout the renewable energy development and utilization chain (REDUC) process. This review also endeavors to structure and assess the contextual landscape of RES optimization modeling research. As evidenced by the literature review, optimization modeling effectively resolves decision-making predicaments spanning RE investment, construction, operation and maintenance, and scheduling. Predominantly, a hybrid model that combines prediction, optimization, simulation, and assessment methodologies emerges as the favored approach for optimizing RES-related decisions. The primary framework prevalent in extant research solutions entails the dissection and linearization of established models, in combination with hybrid analytical strategies and artificial intelligence algorithms. Noteworthy advancements within modeling encompass domains such as uncertainty, multienergy carrier considerations, and the refinement of spatiotemporal resolution. In the realm of algorithmic solutions for RES optimization models, a pronounced focus is anticipated on the convergence of analytical techniques with artificial intelligence-driven optimization. Furthermore, this study serves to facilitate a comprehensive understanding of research trajectories and existing gaps, expediting the identification of pertinent optimization models conducive to enhancing the efficiency of REDUC development endeavors.

Keywords renewable energy system, bibliometrics, mathematical programming, optimization models, solution methods

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List of abbreviations

AI	Artificial intelligence
AHP	Analytic hierarchy process
APSO	Adaptive particle swarm optimization
BESS	Battery energy storage system
BP	Bilevel programming
CCHP	Combined cooling, heating, and power
CDPSO	Chaotic Darwinian particle swarm optimization
CVaR	Conditional value-at-risk
DDRO	Data-driven robust optimization
DE	Differential evolution
DEA	Data envelopment analysis
DL	Deep learning
DNP	de Novo programming
DP	Dynamic programming
DPPO	Distributed proximal policy optimization
DR	Demand response
DRG	Distributed renewable generation
DRL	Deep reinforcement learning
DROCCP	Distributed robust optimization chance constraint programming
DSM	Demand-side management
DSO	Distribution system operator
EFI	Ecological footprint index
ELECTRE	Elimination et choice translating reality
EV	Electric vehicle
FCP	Fuzzy compromising
FIT	Feed-in tariff
FL	Fuzzy logic
FMCDA	Fuzzy multicriteria decision analysis
GA	Genetic algorithm
GEP	Generation expansion planning
GHG	Greenhouse gas
GP	Goal programming
GRG	Generalized reduced gradient
GTEP	Generation and transmission expansion planning
HRES	Hybrid renewable energy system
IoT	Internet of Things
KKT	Karush–Kuhn–Tucker
LCA	Life cycle assessment
LCOE	Levelized cost of electricity
LP	Linear programming
LPSP	Loss of power supply probability
MADM	Multiattribute decision making
MC	Markov chain
MCDM	Multicriteria decision making
MCS	Monte Carlo simulation
MILP	Mixed integer linear programming
MINLP	Mixed integer nonlinear programming
ML	Machine learning
MO	Multiobjective
MODM	Multiobjective decision making
MOGA	Multiobjective genetic algorithm
MOGSO	Multiobjective glow-worm swarm optimization
MOGWO	Multiobjective gray wolf optimizer
MOPs	Multiobjective optimization problems
MOPSO	Multiobjective particle swarm optimization
MOWDO	Multiobjective wind-driven optimization
MPEC	Mathematical program with equilibrium constraints
NLP	Nonlinear programming
NPV	Net present value
NSGA	Nondominated sorting genetic algorithm
OPF	Optimal power flow
PDF	Probability distribution function
PPO	Proximal policy optimization
PSO	Particle swarm optimization
QPP	Quadratic programming problem
RE	Renewable energy
REDUC	Renewable energy development and utilization chain
RES	Renewable energy system
RL	Reinforcement learning
RO	Robust optimization
RPS	Renewable portfolio standard
SAE	Stacked autoencoder
SAIFI	System average interruption frequency index
SD	System dynamics
SP	Stochastic programming
SQP	Sequential quadratic programming
SVR	Support vector regression
TEP	Transmission expansion planning
TOPSIS	Technique for order of preference by similarity to ideal solution
UC	Unit commitment
WOS	Web of Science
WPM	Weighted product model
WSM	Weighted sum model

1 Introduction

To mitigate reliance on fossil fuels and mitigate greenhouse gas (GHG) emissions, nations are adopting a suite of policies to stimulate the advancement of renewable energy (RE). For instance, the European Commission indicated in the 2021 draft amendment to the Renewable Energy Directive that a collective augmentation of the overall share of RE to 40% by 2030 is anticipated (Kougias et al., 2021). Similarly, China, in its "14th Five-Year Plan for Modern Energy Systems" released in 2022, articulated its objective of achieving a rise in the proportion of nonfossil energy consumption to approximately 20% by 2025. The strategic planning and implementation of RE systems (RESs) will steer forthcoming energy systems to be predominantly underpinned by RE (Deng and Lv, 2020). Nonetheless, the functionality of RESs is notably impeded by the nonuniform spatial allocation of renewable resources, the stochastic and uncertain nature of RE advancement, and the challenge of integrating diverse forms of RE power generation (e.g., wind, solar, hydro, and biomass power) (Yan et al., 2023). Moreover, the expansion of RE should not be pursued without due consideration to practical constraints such as cost and technological limitations (Wang et al., 2022). Hence, to ensure the proficient utilization of RE, the enhancement and efficient operation of RESs necessitate the incorporation of economic and technological feasibility aspects, alongside the evaluation of environmental and societal benefits.

An RES can be partitioned into five constituent subsystems founded upon the entire sequence of the renewable energy development and utilization chain (REDUC). These subsystems encompass resource planning and exploitation, production, transmission and distribution, consumption, and storage, as depicted in Fig. 1. Each subsystem is associated with distinct facets of optimal decision-making challenges. For example, within the resource exploitation subsystem, endeavors should be directed toward optimizing site selection and arrangement (Wang et al., 2019), as well as the provisioning of biomass feedstock to augment resource utilization (Sarker et al., 2019). In the realm of the RE production subsystem, judicious planning for power generation, heat supply, and hydrogen synthesis is imperative to ensure maximal efficiency while maintaining harmonious coordination with other subsystems, thereby ameliorating system costs,

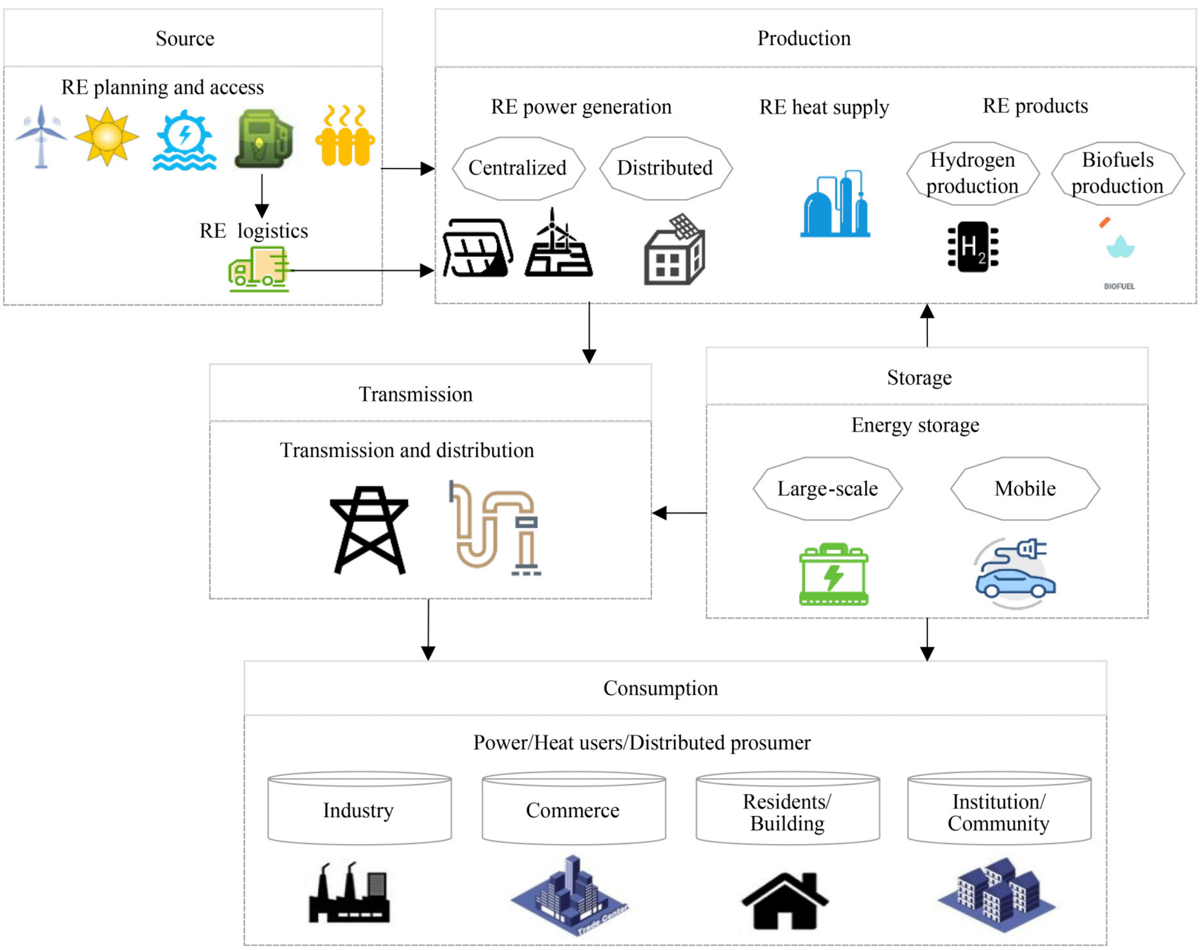

Fig. 1 Components of the renewable energy system (RES) and subsystems.

mitigating investment risks, and curtailing system operation vulnerabilities (Bloess, 2020). To harmonize energy supply and demand, the transmission subsystem catering to RE must be intricately designed, encompassing the layout of transmission and distribution lines, heat conveyance conduits, hydrogen refueling stations, and transportation routes (He et al., 2017; Wei et al., 2018; Shao et al., 2021a; Le et al., 2023; Moradi-Sepahvand et al., 2023). Crafting policies for incentives is vital within the consumption subsystem to minimize the cost of RE consumption, necessitating the strategic enhancement and optimization of consumer propensity toward RE adoption (Wang et al., 2020a). The energy storage subsystem, tasked with the dissipation of peak loads and the optimization of RE utilization efficiency, mandates a rational design and systematic scheduling of the energy storage technology portfolio (He et al., 2020). Within the overarching REDUC framework, synergistic optimizations manifest among subsystems, such as the harmonization between power generation and electricity transmission planning (Yi et al., 2016), multiagent market supervision, optimization of incentive structures, and profit distribution strategies concerning power generation and consumption entities (Come Zebra et al., 2021).

Researchers have formulated distinct optimization models to address the aforementioned facets of decision-making requisites within RES, a subject that has garnered attention in the literature. For instance, Oree et al. (2017) undertook a review of strategies employed to manage conflicting objectives and the uncertainties stemming from stringent environmental policies, power supply sufficiency, and operational flexibility in the context of optimizing RE capacity expansion. Siddaiah and Saini (2016) presented a summary of the configuration of off-grid or grid-connected hybrid renewable energy systems (HRESs), exploring aspects such as technology mix and geographical scope. They also delved into models such as linear programming (LP), dynamic programming (DP), and optimization techniques such as the genetic algorithm (GA). In the context of technological selection flexibility for RESs, Luo et al. (2015) examined the categorization and diverse application scenarios of electric energy storage technologies. Furthermore, Esther and Kumar (2016) provided an overview of existing demand-side management (DSM) optimization models, elucidating their classification, objectives, and constraints, particularly in the context of residential demand response (DR) for enhancing flexibility. Correspondingly, Bloess et al. (2018) evaluated the potential flexibility offered by power-to-heat technologies, considering both technical possibilities and mathematical optimization modeling procedures. Yu et al. (2022) conducted an analysis encompassing renewable power generation uncertainty, impacts on grid connection, and techno-economic performance within the framework of transmission expansion planning (TEP). Similar reviews have addressed various aspects of RES, including cost-effectiveness (Crespo del Granado et al., 2018), technical diffusion (Zhou et al., 2021), environmental performance (Bertasini et al., 2023), prediction errors (Ahmad et al., 2020), and uncertainty (Zakaria et al., 2020).

This body of literature has been aptly categorized, offering an elucidation of optimization issues within RES. These encompass modeling characteristics and the identification of prospective avenues for future advancement. However, there exists a notable gap in terms of a comprehensive review that offers a holistic optimization analysis, encompassing the entirety of the RE development and utilization process. Furthermore, a generalization of solution methodologies applied to these models is also lacking. Moreover, most investigations concerning the models and techniques pertinent to the aforementioned issues primarily focus on optimization frameworks, scenario analyses, and the utilization of energy system modeling tools such as MARKAL and Long-range Energy Alternatives Planning (LEAP) (Plazas-Niño et al., 2022). Furthermore, a more systematic approach is necessary for reviews of RES. In light of these gaps, this study embarks on a comprehensive examination of optimization modeling and solution methodologies featured in the literature, encompassing the entire REDUC process, underpinned by bibliometric analysis.

This review's contributions are outlined as follows: First, the division of subsystems facilitates a comprehensive and contemporary survey of optimization challenges within RES, thereby facilitating a thorough understanding of the merits and demerits of different models and solution methodologies, along with their suitability for specific decisions. Second, this study offers a generalization of optimization techniques, pinpointing modeling criteria and juxtaposing model and algorithm characteristics, thereby enhancing researchers' comprehension of the process, principles, and procedural steps involved in RES modeling. Finally, this study offers insights into potential research directions and decision-making guidance for the future. It serves to elevate the application of optimization modeling and advanced solution methodologies within the realm of RES, particularly in the context of substantial RE penetration.

The subsequent sections of this study are organized as depicted in Fig. 2. Section 2 furnishes an overview of published papers through the application of text-mining-based bibliometric analysis. In Section 3, a comprehensive exposition of decision-making predicaments and pragmatic scenarios for optimization models throughout the REDUC process is presented. This section also delves into modeling criteria. Building upon these criteria, Sections 4 and 5 examine and compare the characteristics and potential applications of optimization models and solution methodologies. Finally, the study concludes by introducing overarching findings and outlining future trends in Section 6.

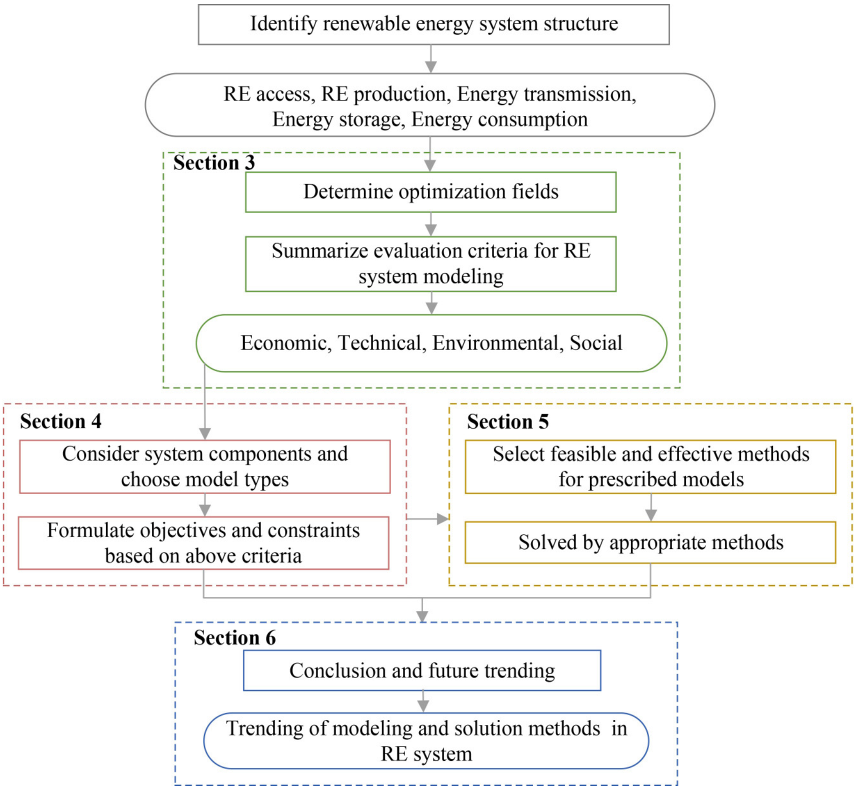

Fig. 2 General procedure and flowchart of RES optimization.

2 Bibliometric analysis

In the context of this review, the Web of Science (WOS) database was chosen as the primary source. The search query #1 AND (#2 OR #3 OR #4) outlined in Table 1, with the inclusion of the SCI-expanded, SSCI, and CPCI-S indexes, was employed to scrutinize a total of 22341 pertinent papers, conference proceedings, and reviews spanning the timeframe from 1990 to 2023 (as of February 18, 2023).

The publications and citations of the past decade are depicted in Fig. 3. As observed, the predominant portion consists of journal articles (63.22%). Earlier papers exhibit higher citation rates, reaching their zenith in 2018. The mean number of citations per article is 24, displaying fluctuations between 2003 and 2014.

Figure 4(a) illustrates the publication and citation landscape of the top 10 journals. Notably, *Renewable & Sustainable Energy Reviews* and *IEEE Transactions on Smart Grid* emerge prominently, with average citation counts of 76 and 55, respectively. In Fig. 4(b), the predominant term "Renewable energy" takes center stage, while the preeminent field proves to be "Energy & Fuels".

The author keywords are organized into clusters using VOSviewer, employing a co-occurrence frequency threshold set at more than 15 instances. Figures 5(a) and 5(b) present network visualizations of keyword clustering occurrences and average overlays per year. In Fig. 5(a), Cluster 1 is focused on RE management and scheduling, encompassing topics such as energy storage, smart grid, electric vehicles (EVs), load management, energy sharing, and game theory as auxiliary studies. Cluster 2 centers on RE optimization scenarios, aided by studies related to

Table 1 Research results from the WOS search

Number of articles	WOS search categories	Keyword equations
32806	Topic	#1 TS=(((renewable energy) OR (renewable power) OR (renewable electricity) OR (renewable heat*)) AND (optimiz*))
20261	Abstract	#2 AB=(((renewable energy) OR (renewable power) OR (renewable electricity) OR (renewable heat*)) AND (optimiz*))
1044	Title	#3 TI=(((renewable energy) OR (renewable power) OR (renewable electricity) OR (renewable heat*)) AND (optimiz*))
3247	Author keywords	#4 AK=(((renewable energy) OR (renewable power) OR (renewable electricity) OR (renewable heat*)) AND (optimiz*))
22341	Total articles	#1 AND (#2 OR #3 OR #4)

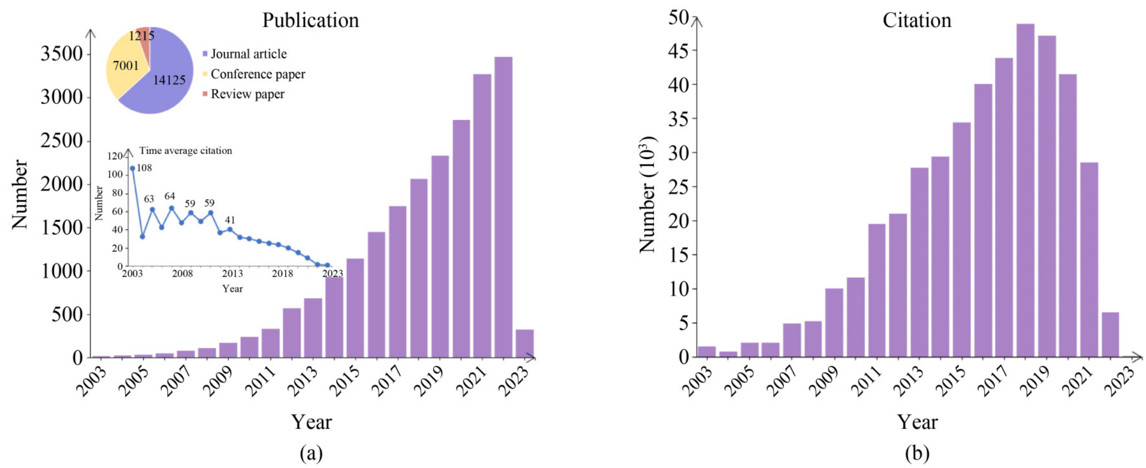

Fig. 3 (a) Publications, (b) Citations, and article type (pie chart) and citation of a single article on average (point and line) in (a).

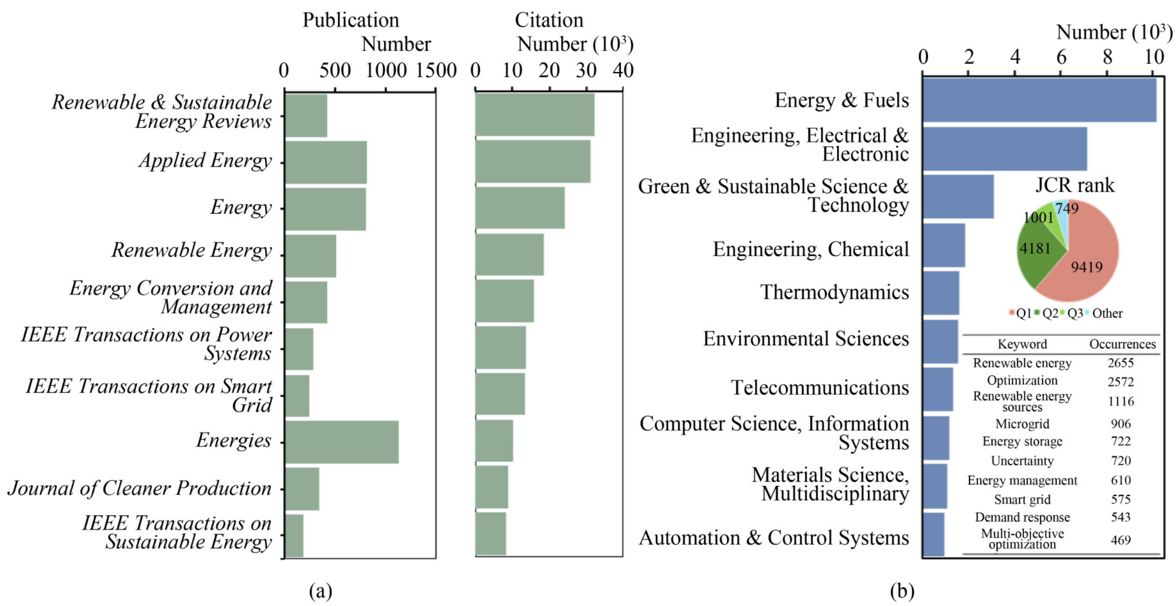

Fig. 4 (a) The most popular journals by publications and citations; (b) Most popular research areas, JCR rank, and most popular keywords.

energy supply and operation within integrated RES, hydrogen energy, hydrogen production processes, sustainability, efficiency, and energy policy. Cluster 3 revolves around HRES scale and cost optimization, amalgamating methodologies such as techno-economic analysis, sensitivity analysis, and life cycle assessment (LCA) to mitigate the risks in energy optimization decisions. Cluster 4 concentrates on RES optimization algorithms, including particle swarm optimization (PSO), GA, and fuzzy logic (FL). Cluster 5 is concerned with multimicrogrid modeling and encompasses issues such as unit commitment (UC), economic dispatch, and voltage control, emphasizing system reliability and stability studies. In Cluster 6, with increased system uncertainty, the focus shifts toward microgrids (MGs) and distributed renewable generation (DRG) system modeling, underscored by the flexible employment of multicriteria decision making (MCDM), stochastic programming (SP), and robust optimization (RO).

Figure 5(b) portrays the evolution of keywords over time, serving as a tool for analyzing trends in hot keywords across years. Before 2017, research primarily delved into modeling methods for various RE sources. Analytical methods centered on optimization modeling, simulation, and assessment, with tools such as Hybrid Optimization of Multiple Energy Resources (HOMER) playing a significant role. From 2017 to 2019, the focus transitioned toward enhancing energy efficiency and auxiliary services within multienergy systems. During this period, research attention shifted from individual RE sources, hydrogen energy, RE efficiency, and intelligent algorithms to encompass energy storage, MGs, EVs, DSM, and energy policy. This phase saw an expansion toward the latter stages of the REDUC. Between 2019

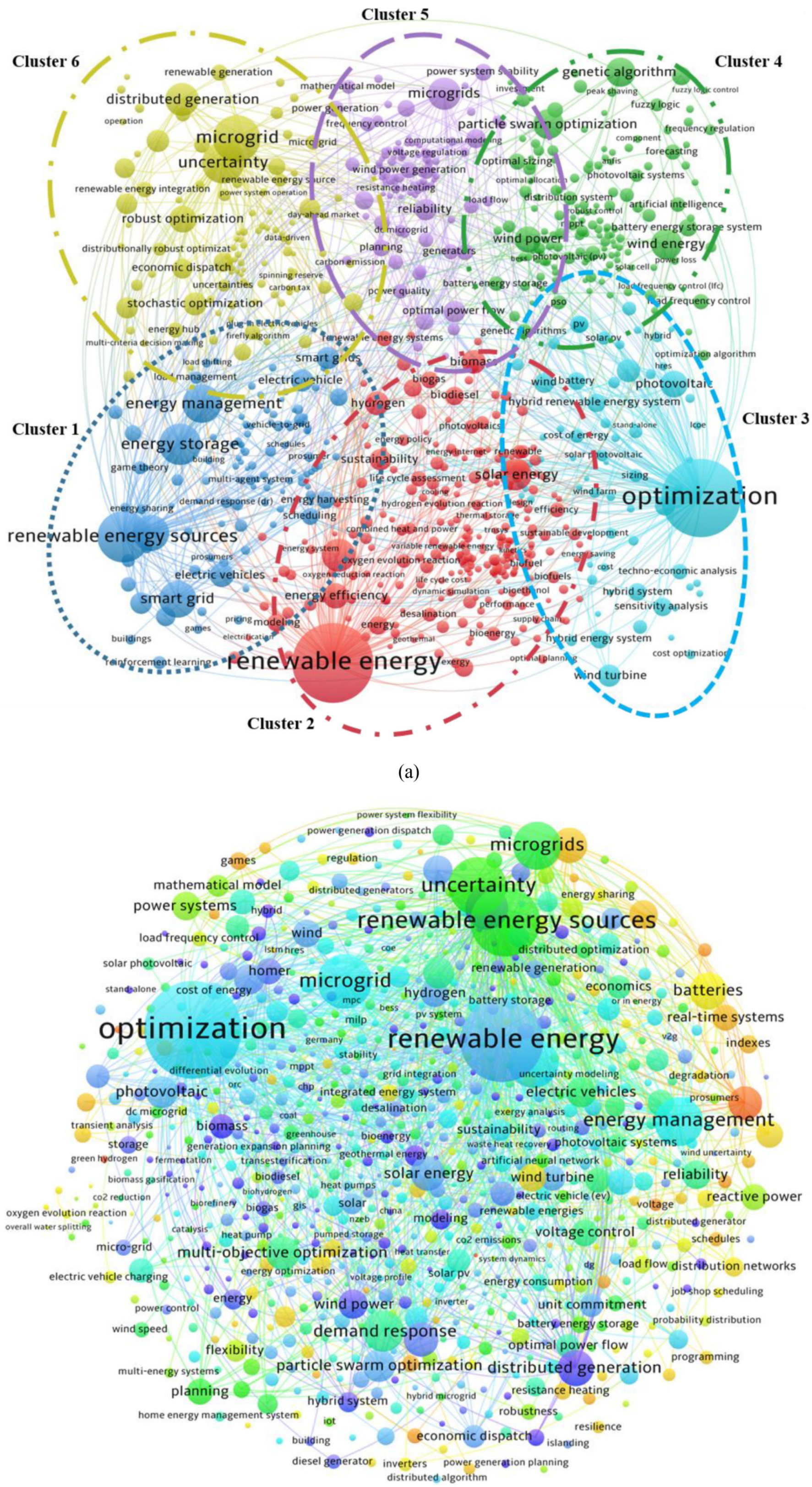

Fig. 5 (a) Network visualization occurrences; (b) Overlay visualization average publication per year occurrence for author keywords in all fields.

and 2020, the research emphasis turned toward refining energy modeling methods in the context of deep decarbonization while also incorporating multiobjective (MO) optimization. There was rapid progress in methodologies such as Benders decomposition, distributed optimization, machine learning (ML), and neural networks (NNs). Moreover, topics related to RES security, reliability, and uncertainty gained traction, and new areas such as DR, MGs, battery energy storage systems (BESS), decarbonization, and the water-energy nexus emerged.

Over the past three years, with the advancement of modeling techniques and the proposition of China's "Dual Carbon" objective, research has increasingly focused on real-time RE dispatch and modeling uncertainties on the demand side, emphasizing the influence of human factors. Green hydrogen has gained significance due to its role in the deep decarbonization of RE consumption. The theme of cost remains constant, especially within programming models, including the deployment and enhancement of RE infrastructure. Carbon neutrality, load modeling, predictive modeling, real-time systems, game theory, information gap decision theory, probabilistic logic, and peer-to-peer computing have emerged as new focal points, offering diverse data-driven tools for optimizing RES. As research becomes more saturated and topic boundaries expand, new contexts, such as the energy policies of major countries, are receiving increased attention. Furthermore, there is a discernible trend toward more comprehensive, refined, and intelligent hybrid models and methodologies in research orientations.

3 Overview of optimization fields in the RES

3.1 Optimization problems and potential scenarios

Building upon the insights presented in Fig. 1, which illustrates the division of RES, the optimization problems and their corresponding models across all phases of the REDUC can be systematically categorized, as depicted in Fig. 6.

The optimization process within the RE development planning and exploitation stage encompasses activities such as evaluating the potential, setting development goals, and optimizing plant location and layout. This stage takes into account factors such as resource availability (Salehin et al., 2016), investment estimation (Ziemba, 2022), and analysis of environmental and social impacts (Li et al., 2020a). The evaluation of RE potential is undertaken using methods such as MCDM and deep learning (DL) models, which are applicable at regional, national, and global scales. Examples include assessing the photovoltaic (PV) potential in Wuhan, China (Zhang et al., 2021a), wind power potential in India (Saraswat et al., 2021), and a global inventory of PV generation (Kruitwagen et al., 2021). Models such as hybrid MCDM and fuzzy LP are utilized for site optimization and the optimal design of biomass transportation networks (Sarker et al., 2019). Additionally, the investment decisions for planned wind farm projects in Poland are made employing the fuzzy multicriteria decision analysis (FMCDA) method (Ziemba, 2022).

The RE production stage focuses on optimizing the generation of renewable electricity, heat, or processing methods. This may involve proposing uncertain renewable power system planning models to amplify RE generation (Chen et al., 2020b). Traditional power plants, including thermal power plants, are adapted to align with the variable RE output (Li et al., 2016; Zhu et al., 2021). Moreover, the decommissioning of wind farms and PV panels may be undertaken (Hoti et al., 2021; Mackie and Velenturf, 2021).

Optimization within the energy transmission stage centers on planning and scheduling the configuration of transmission and distribution systems, considering the integration of technologies and mechanisms for stability control (Keane et al., 2013; Yu et al., 2022). Notably, nonlinear transmission expansion models optimize network layout and capacity across regions in China (Yu et al., 2022).

Efforts directed toward optimizing the energy consumption stage involve scheduling between subsystems, equitable distribution of benefits among market agents (such as generators, transmitters, distributors, and marketers), and designing and operating distributed RESs (Chennaif et al., 2022) and MGs (Huy et al., 2020). Furthermore, research addresses the consequences of implementing RE public policies and explores optimal pathways (Watts et al., 2015; Siddiqui et al., 2016). For instance, Ding et al. (2020) developed a DP model to optimize the feed-in tariff (FIT) price in China, supporting RE technologies.

The optimization of the energy storage stage concentrates on configuring energy storage systems and devising operation strategies for the generation, grid, and demand facets (Denholm and Margolis, 2007; Yang et al., 2020). Models such as LP or mixed integer linear programming (MILP) are employed to optimize the configuration and timing of novel energy storage systems (such as electrochemical and hydrogen storage) (Parrish et al., 2019). These models extend to designing energy storage systems for European countries (Cebulla et al., 2017), the IEEE Reliability Test System (Hannan et al., 2020), and investigating arbitrage behavior and profits (Chen et al., 2021).

In addition to optimizing individual subsystems, some studies extend their scope to optimizing the entire RES. For instance, the EnergyPLAN modeling tool was used to optimize an economically viable configuration for a 100% renewable smart energy system across Europe's power, heating, cooling, and transportation sectors (Connolly

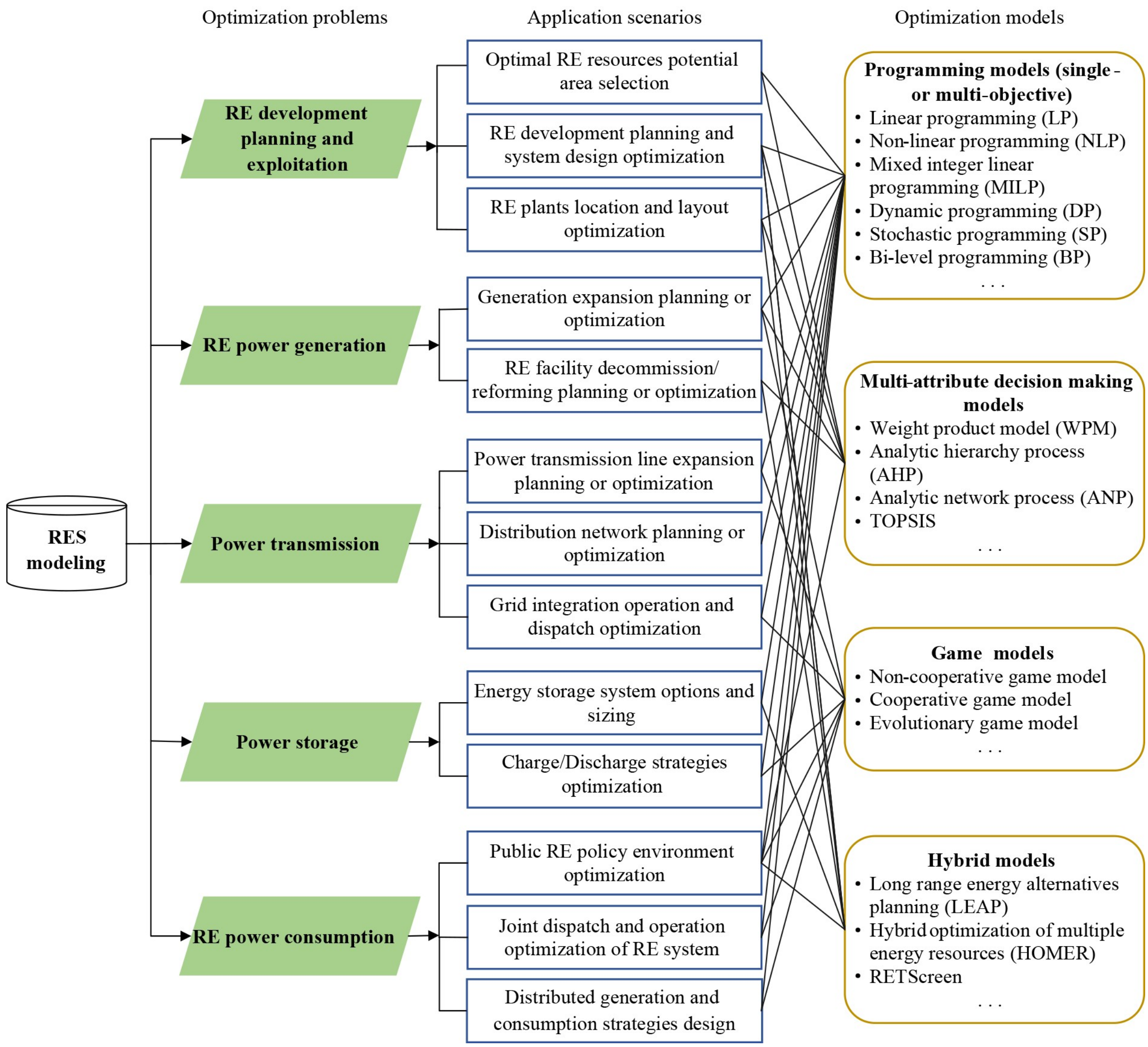

Fig. 6 RES modeling in the optimal planning and operation of subsystems.

et al., 2016). Similarly, multiagent game models (Chuang et al., 2001) and general or partial equilibrium models (Jaskólski, 2016) are applied throughout the RES to achieve optimization objectives.

3.2 Optimization modeling criteria for RES

The modeling of RES optimization decisions is commonly grounded in economic, technical, social, and environmental objectives and constraints (Atabaki and Aryanpur, 2018), as outlined in Table 2. Economic considerations entail evaluating costs or profits. Technical aspects encompass stability and safety assessments (Memon et al., 2021). Social criteria encompass metrics such as the number of jobs (Atabaki and Aryanpur, 2018) to gauge factors such as employment opportunities, energy security, societal well-being, and policy implications. Environmental criteria are intricately linked to aspects such as CO_2 emissions, temperature control targets, and biodiversity preservation (Edwards and Trancik, 2022). Addressing the trade-offs that arise between numerous criteria becomes essential during the modeling process for reaching decisions within RESs. For instance, elevated technical requisites may yield increased employment and reduced emissions but result in higher costs. Security and reliability typically take precedence over economic gains in power transmission and microgrid design (Dehghan and Amjady, 2016). Conversely, greater profits are favored in market transactions, DSM, and distribution scheduling (Acuña et al., 2018).

4 Optimization models in the RE system

The optimization models encompassed within this review span various methodologies, including programming (both single- and multi-objective), multiattribute decision making (MADM), game models, and hybrid optimization

Table 2 Summary of evaluation criteria in RES modeling

Decision objective	Criteria/Constraint	Description
Economic	Total annual cost or annual system cost (Xuan et al., 2021)	All costs for capital, installation, operation, and delivery
	Net present value (NPV) (Li et al., 2016; Tezer et al., 2017)	The sum of lifetime incoming and outgoing cash in the form of discounted present values
	Levelized cost of electricity (LCOE) (Memon et al., 2021; Chennaif et al., 2022)	For generation: The ratio of total antioxidant capacity (TAC) to the total generated energy For storage: Costs and energy consumed per operating hour
	Life cycle cost (Tezer et al., 2017; Chennaif et al., 2022)	All expenses are expected to occur, except manufacturing and disposal costs
	Life cycle unit cost (Tezer et al., 2017)	Unit energy cost is calculated by dividing life cycle cost by the total energy produced
	Cumulative savings (Afful-Dadzie et al., 2017)	Sum of money saved due to fuel saving
	Fuel consumption (Gbadamosi et al., 2018; Xu et al., 2020)	The total amount of energy consumption by nonrenewable plants
	Learning rate (Yu et al., 2022)	The cost reduction path of RES-related technologies
Technical	Loss of power supply probability (LPSP) (Feng et al., 2018; Memon et al., 2021)	The probability of load deficit over total energy produced
	Difference in net loads (Feng et al., 2018)	Load shifting capacity to smooth the difference between load peaks and valleys
	Loss of load risk (Sinha and Chandel, 2015)	The probability of failure to meet daily energy demand for RE generation
	Loss of energy or load hours expectation (Tezer et al., 2017)	The excepted number of hours for energy or load deficit, exceeding available generation capacity, excluding breakdown and maintenance time
	Unmeet load (Sinha and Chandel, 2015; Dehghan and Amjady, 2016)	The ratio of unsatisfied load to total load after consuming power generation and storage
	Loss of power produces probability (Feng et al., 2018)	Expected probability of energy surplus
	Variable renewable energy (VRE) curtailment rate (Peker et al., 2018; Xu et al., 2020)	Maximum VRE share allowed to be curtailed
	Renewable energy penetration (Liu et al., 2022a)	The ratio of energy generated from RE to total load demand
Social	Job creation (Al-Falahi et al., 2017; Atabaki and Aryanpur, 2018)	Job amounts created by RES, including manufacturing, installation, and operation and maintenance (O&M), throughout the lifetime of components
	Human Development Index (Al-Falahi et al., 2017)	A country development indicator considering life expectancy at birth, years of schooling, and average national income, related to power consumption
	Herfindahl–Hirschman Index (HHI) or Shannon–Weiner Index (Grubb et al., 2006)	Describe diversification of the energy matrix
	Social acceptance (Stigka et al., 2014)	Social performance evaluation criteria to consider social resistance to the installation of RES
	Social cost of carbon (Koltsaklis et al., 2014; Xu et al., 2020)	An additional cost is imposed on society
Environmental	Total CO_2 or fuel emission (Atabaki and Aryanpur, 2018; Hu et al., 2019)	The total amount of CO_2 emissions produced by the system
	Land use (Wang, 2023)	The area of renewable power related land
	Ecological footprint index (EFI) (Fakher et al., 2023)	The comprehensive resource pressure of environmental degradation
	Life cycle assessment (Li et al., 2011; Yu et al., 2019)	The cost includes pollution, health effects, and environmental impacts

models. Across the five-subsystem optimization challenge presented by the REDUC framework, single-objective models find extensive application in tasks such as plant site layout, generation and transmission expansion planning (GTEP), storage deployment, charging/discharging strategies, and optimization of distributed grid-connected consumption issues (Ramakumar et al., 1986; Wang et al., 2020a). MADM models are frequently employed for RE resource assessment and subsystem planning, primarily due to their capacity to handle concurrent conflicts (Atabaki and Aryanpur, 2018). Game models exhibit a robust capability to encapsulate planning and operational predicaments involving the divergent interests of distinct agents or stakeholders (Jenabi et al., 2013). Optimization models are effectively integrated with prediction models, system simulations, and assessment models. For instance, the nonlinear mapping capabilities of NNs can be harnessed to optimize the planning of RESs, relying on forecasts of wind and solar power output, as well as load levels (Mertens et al., 2021).

Figure 7 illustrates the overarching framework for modeling RES optimization. The selection of an appropriate model type hinges on the inherent characteristics of the problem at hand. Subsequently, parameters such as spatial and temporal resolution, as well as energy demand, are precisely defined. Following this, decision variables pertaining to installation choices and installed capacities, along with objective values encompassing parameters such as total cost, RE power supply, and GHG emissions, are ascertained.

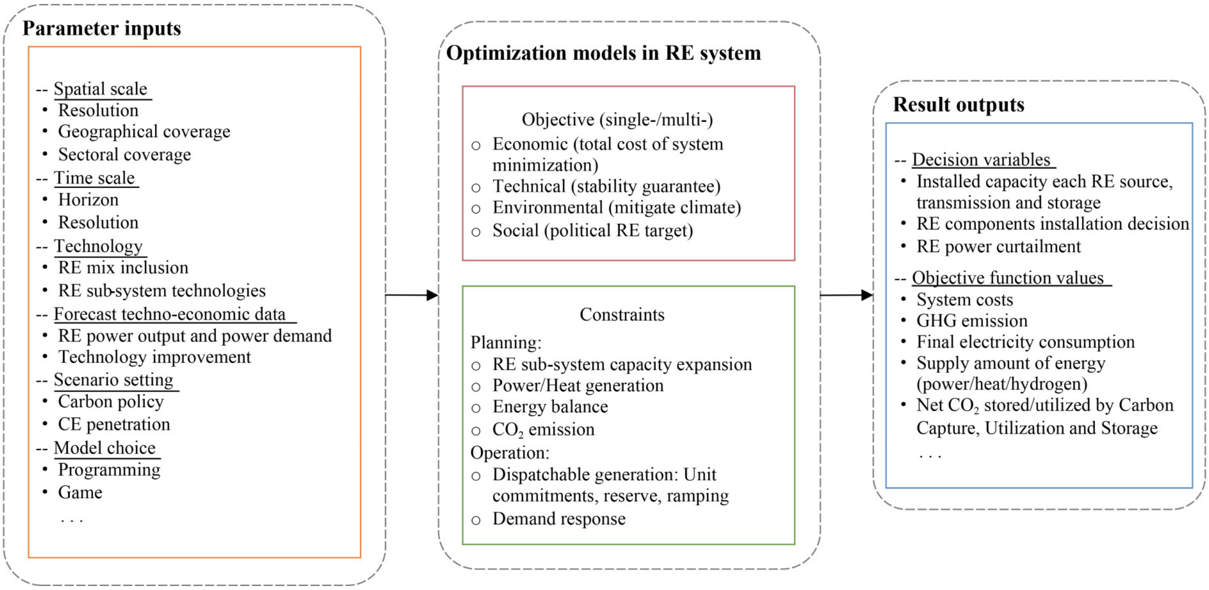

Fig. 7 Framework of optimization models in RES.

4.1 Programming models (single- and multi-objective)

Programming models within the realm of RES are predominantly rooted in economic considerations. Consequently, the optimization of RES decisions is commonly structured as a programming model aimed at minimizing resource consumption or maximizing economic gains, as depicted in Fig. 8.

Given the widespread acceptance of sustainable development principles, optimization objectives for RESs encompass not only economic factors but also technical, environmental, and social considerations. However, these objectives frequently stand in contrast to one another. Consequently, achieving the best possible outcomes for all objectives necessitates compromises, resulting in a Pareto optimal solution (Coello Coello, 2006). In contrast to single-objective programming models, MO models prove more realistic, as they concurrently account for multiple evaluation aspects, akin to the complex nature of actual decision-making processes. This is articulated through the inclusion of objective functions rather than being restricted to economic indicators or constraints (Mavrotas et al., 1999).

4.1.1 Linear programming

Linear equations or inequalities serve as the objective functions and constraints in LP mathematical models (Dantzig, 2002). When modeling RESs, variables are typically assumed to be linear or approximately linear, rendering LP a widely applicable and convenient method for resolution. Objectives that aim to curtail overall costs are frequently employed (Ramakumar et al., 1986). Constraints encompassing factors such as resource potential, investment budgets, and outage rates are typically expressed using energy policy parameters (Frew et al., 2016; Yu et al., 2021) and linearized relational equations (Li et al., 2016). The utilization of LP is extensive in RES optimization, particularly for tasks such as generation expansion planning (GEP) across various countries and regions. For instance, Liu et al. (2009) devised a MESSAGE-China LP model to design a combination of solar, biomass generation, and carbon capture and storage (CCS) technologies for the purpose of cost minimization. Neumann and Brown (2021) employed the LP model to optimize a European power system striving for 100% RE integration.

Incorporating macro policies’ influence on GEP decisions often entails introducing policies as linear constraints in the LP model. For instance, Wang et al. (2020a) considered scenarios involving renewable portfolio standards (RPS) and developed a mid- and long-term optimization model for the RE power system within China’s Southern Power Grid. Goop et al. (2017) approached PV generation policies involving RPS and FITs, developing a linear model for investment cost minimization and power dispatch.

Moreover, LP models have found utility in optimizing the siting of RE power plants. Jeong and González-Gómez (2020), for example, formulated a Fuzzy LP model to evaluate site suitability and select locations for five biomass power plants. Additionally, de Laporte et al. (2016) explored the influence of biomass prices on feedstock supply in Ontario, Canada, employing an economic LP model.

In scenarios where multiple conflicting objective functions are at play, LP transitions into an MO LP framework, incorporating constraints in the form of linear equations or inequalities. Such models typically consider various objectives, such as economic cost and RE

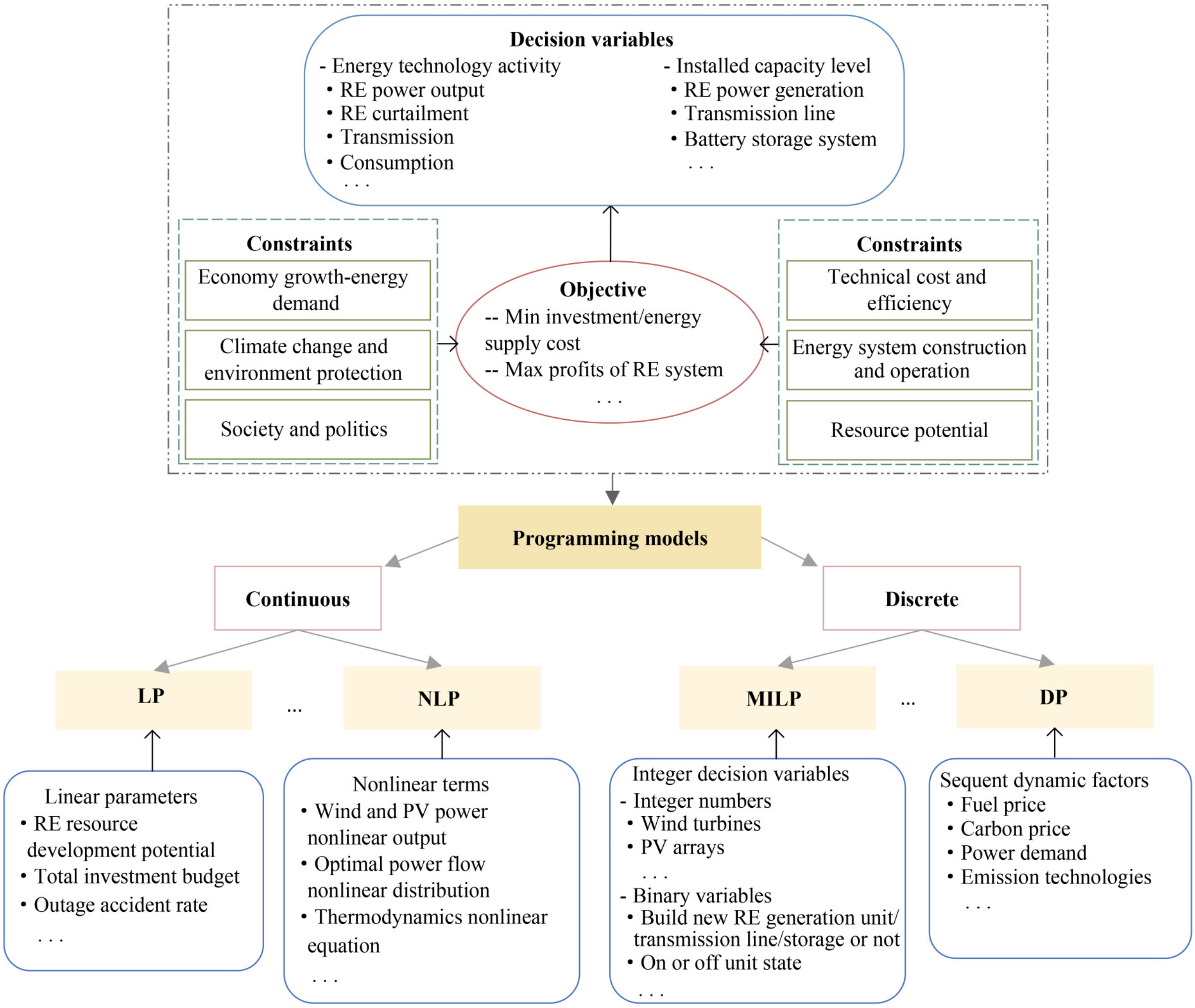

Fig. 8 Principle of programming models in RES.

consumption ratio (Karaki et al., 2002; Bakhtavar et al., 2020). For instance, Chen et al. (2015) addressed power generation, total cost, and CO_2 emissions as objectives within the GEP problem. Karaaslan and Gezen (2022) employed MO LP models with interval coefficients for unit investment scheme optimization. Yu et al. (2019) developed a fuzzy MO optimization model for renewable power system planning in China, seeking to minimize investment costs, maximize RE utilization hours, and achieve maximum life cycle carbon emission reduction.

4.1.2 Nonlinear programming

LP hinges on precise data accuracy and solely accommodates linear relationships among variables (Razavi et al., 2019). However, objectives or constraints in RES decision problems frequently exhibit nonlinear relationships, particularly within optimization scenarios involving dispatch operations encompassing distribution networks and MGs. This is notably relevant to optimal power flow (OPF) and node voltage control (Kannan et al., 2005). For instance, Brown et al. (2016) introduced a nonlinear OPF problem into a European power system optimization model. The nonlinear objective or constraint functions inherent to nonlinear programming (NLP) models give rise to nonconvex feasible regions (Razavi et al., 2019). Consequently, it is plausible that the optimal local solution may not necessarily be globally optimal. Thus, alongside numerically determining the optimal value, the optimization process necessitates assessing the accuracy of the results. The consideration of exact penalty methods, such as measuring constraint infeasibility, has been explored in this regard (Gonzaga et al., 2004).

Within RESs, the broader resource scheduling challenge remains an NLP problem, even in the absence of the OPF component. For instance, Xu et al. (2020) established a 24-hour dispatch model for wind-battery HRES that addresses wind power curtailment and investor interests by incorporating the nonlinear aspect of battery degradation costs. Similarly, Wang et al. (2020c) devised a nonlinear objective function for minimizing operating costs and risks to tackle the coordination problem of combined cooling, heating, and power (CCHP) MGs.

The scope of the objective function can be extended to encompass multiple conflicting objectives. Liu et al. (2022b) formulated a nonlinear MO optimization model to optimize distributed energy system configurations and energy storage system operation strategies, taking into account considerations such as carbon emissions, costs, and network interactivity. In addressing RE abandonment within a wind-solar-coal dispatch system, Tan et al. (2019) adopted objectives that encompass total costs and the rate of RE spillage.

4.1.3 Mixed integer linear programming

The transformation of the LP problem into an MILP problem arises when integer variables are introduced into the decision variables (Gomory, 2010) within the context of RESs. Examples include employing binary 0–1 variables to determine the installation or construction of new lines (Afful-Dadzie et al., 2017), regional interconnections (Koltsaklis et al., 2014), storage charging and discharging strategies (Moradi-Sepahvand and Amraee, 2021b), and unit on and off states (Bakirtzis et al., 2012). Macro models frequently hinge on linear equations. Binary decision variables are frequently utilized to extend transmission system optimization, signaling whether a transmission line should be established (Gbadamosi et al., 2018). The optimization of facility capacity involves the investment costs of generating units and transmission lines as the objective function (Li et al., 2020b). The MILP model explicitly takes financial constraints into account to prevent costly emergency plans and mitigate the risk of disrupted unit investments (Afful-Dadzie et al., 2017).

Beyond decisions related to infrastructure expansion, integer variables encompass decommissioning decisions (Bakirtzis et al., 2012) and operational choices (Chen et al., 2020a). MILP approaches can also delve into impact assessment and feasibility analyses (Shu et al., 2017). In their examination of decommissioning decisions within the Greek renewable power system, Bakirtzis et al. (2012) devised an MILP model incorporating binary variables to represent the old units eligible for refurbishment. MILP models are also constructed for generation-transmission-storage co-optimization, featuring binary variables to indicate BESS construction, as well as charging or discharging statuses (Moradi-Sepahvand and Amraee, 2021b). Similarly, decisions pertaining to the techno-economic viability of RE options can be addressed. For instance, Liu et al. (2016) employed an MILP model to optimize and assess biomass combined combustion technology in Missouri, USA.

In conjunction with MO optimization, the amalgamation of objectives leads to the formation of mixed integer MO optimization models. For example, Lotfi et al. (2022) established objectives encompassing the maximization of government energy production and supplier profits to optimize the siting of RE sources. Binary decision variables indicated whether to deploy RE and, if so, the chosen type. Similarly, Ghaithan et al. (2022) determined the quantities of PV modules and wind turbines, aiming to minimize total life cycle costs, GHG emissions, and the share of grid contributions.

4.1.4 Dynamic programming

DP models exhibit an optimal substructure while lacking Markov properties, underscoring the criticality of defining problem states and state transition equations (Akella et al., 2007). The crux of the DP challenge involves partitioning and resolving redundancy, thereby streamlining the size of the solution space. This approach resembles the top-down greedy algorithm (Li et al., 2014). In the realm of RES decision optimization, DP models find extensive utility, particularly in scenarios infused with risks and uncertainties (Lu et al., 2016), as depicted in Fig. 9. The notion of a stage manifests in the multistage aspect of DP when it is structured based on temporal or spatial considerations. The term "state" pertains to the variable values and characteristics associated with a particular stage (Putz et al., 2021). Consider GEP DP, where the stage represents the decision-making timeframe, the number of newly constructed units delineates the path, and the cumulative unit count signifies the state. Constraints within the model can be classified into two groups: Path-related constraints and state-related constraints (Su et al., 2000).

In macro-optimization scenarios for RESs, DP applications often incorporate changes in external conditions to define the state. As an example, Afful-Dadzie et al. (2017) introduced a dynamic model for GEP in developing countries. They identified two stages, each corresponding to the time when actual demand, constrained by budget considerations, materialized. The quantity and capacity of generators constituted the "here and now" decision variables, while generation, imported power, and unmet demand in the subsequent phase were deemed "wait and see" decision variables. Mertens et al. (2021) devised a DP model based on estimated carbon prices and annual electricity demand for medium- to long-term power system planning. Lu et al. (2016) proposed a DP model for GEP grounded in conditional value-at-risk (CVaR) theory, deploying it in a regional grid case within China to address the trade-off between benefits and risk control.

In the context of RES micro-operation optimization using DP, technical challenges such as UC, distribution network considerations, and feeder line optimization frequently arise. This calls for the inclusion of physical characteristics encompassing the variability of RE resources and power output, as well as voltage and current parameters in grid operation. For instance, Li et al. (2014) effectively employed DP to capture hydraulic connectivity and water balance, optimizing the dynamic operation of large-scale hydropower dispatch in the

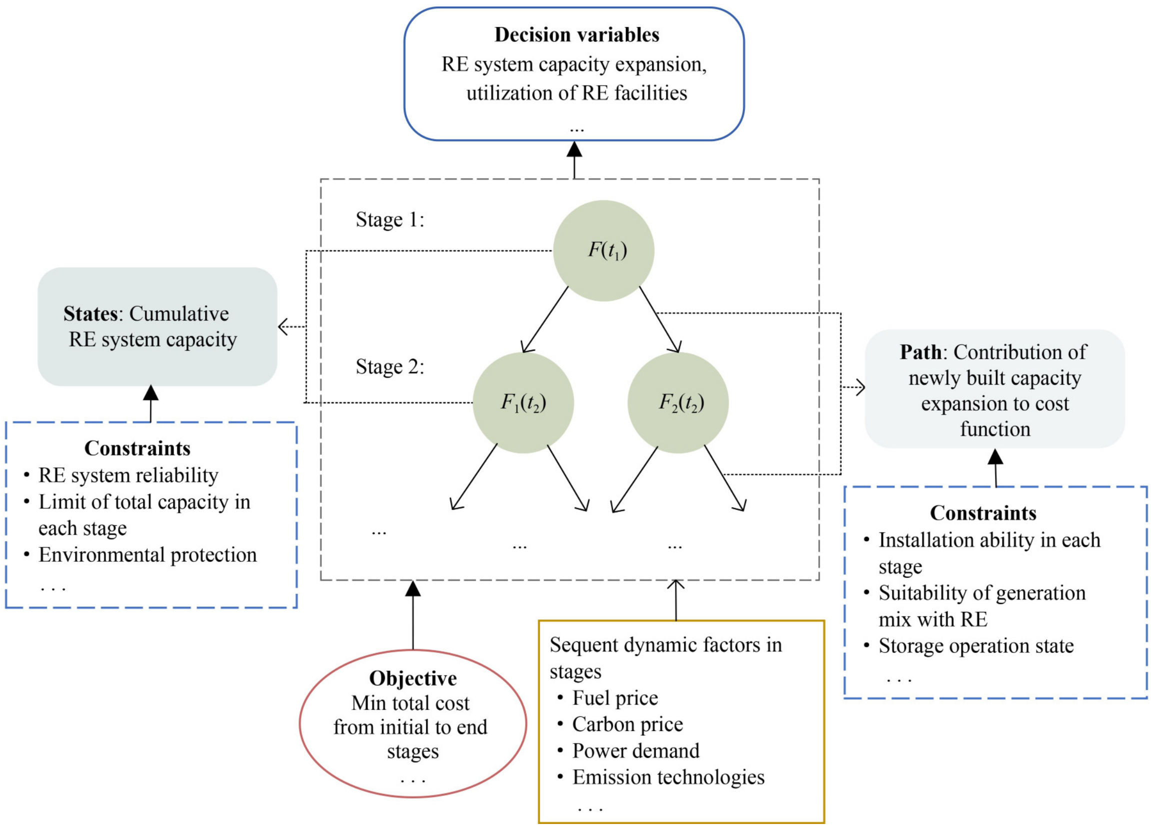

Fig. 9 Dynamic programming models in RES.

Yangtze River. Employing the state space of cost under variable RE power and generation, Putz et al. (2021) implemented backward DP with state prediction, decomposing the problem into smaller subproblems to address the discrete UC issue in Austria.

Moreover, DP finds application in distribution network planning to address optimization challenges related to technology selection and sizing. For example, Boulaxis and Papadopoulos (2002) introduced a DP model to optimize optimal feeder routing. Borges and Martins (2012) adopted the Backward Path and Forward Path techniques to formulate multistage problems, establishing a DP model for planning distributed active distribution networks. Similarly, Muñoz-Delgado et al. (2016) established a multistage cost-minimizing dynamic planning framework grounded in stochastic scenario simulations of RE generation and demand uncertainty.

DP rooted in MO optimization augments comprehensive economic, environmental, and social considerations while accounting for technical attributes. Sharma et al. (2022) developed an MO DP model to optimize the trading strategy of HRESs in collaboration with the grid. The model encompassed dynamic aspects such as wind and PV output characteristics, along with load profiles, while minimizing operating costs, non-RE utilization, and fuel emissions. Das et al. (2021) optimized real-time charging/discharging strategies for EVs within residential settings driven by RE sources.

4.1.5 Stochastic programming

SP models constitute an extended version of LP, specifically tailored to scenarios in which the coefficients or parameters are treated as random variables. This framework finds application in handling uncertainty-based decisions within RESs (Abdalla et al., 2019). The introduction of random distributions into the optimization model is typically accomplished through the utilization of probability distribution functions (PDFs), which capture the stochastic nature inherent in RESs (Zakaria et al., 2020). Instances include wind speed fluctuations, energy price variations, demand uncertainty, and unanticipated system risk factors. For instance, Namilakonda and Guduri (2021) harnessed Latin hypercube sampling to generate uniform random samples of wind speed and solar radiation within a stochastic power system dispatch model. Abdalla et al. (2019) utilized PDFs to calculate the probabilities of uncertainty scenarios, thereby predicting solar radiation, environmental temperatures, and wind speeds for RES applications.

Moreover, RO serves as a complementary counterpart to SP, offering outcomes endowed with robustness and worst-case applicability without necessitating assumptions about parameter distributions (Zakaria et al., 2020). RO techniques have been employed for planning tasks, including addressing uncertainties associated with loads and wind power generation (Dehghan and Amjady, 2016).

Wang et al. (2020c) established conditional risk operational constraints under RO scenarios, ensuring the safety and stability of CCHP MGs.

Stochastic MO optimization models extend beyond single-objective planning models. Zandrazavi et al. (2022) minimized stochastic MO models incorporating total cost and voltage deviation indices, tackling the issue of microgrid grid imbalances. They generated scenarios encompassing uncertainty using a roulette mechanism to account for RE generation, EV charging demand, electricity load, and electricity prices. In the context of RE site optimization, Lotfi et al. (2022) adopted a data-driven robust optimization (DDRO) approach that augments the energy and profit objectives (pertaining to government and supplier interests) with minimum functions, thereby accommodating risk considerations.

4.1.6 Bilevel programming models

MO optimization offers a comprehensive approach that thoroughly considers the solutions for each objective function, yielding comprehensive results. However, in the realm of bilevel programming (BP), objectives cater to distinct decision-makers. Optimization progresses in an alternative manner, based on the outcomes of preceding optimization steps (Lotfi et al., 2021), as illustrated in Fig. 10. Variables within the objective function are subjected to constraints that enforce them to be optimal solutions of another optimization problem. Put differently, the parameters of the primary problem are bound by constraints to optimize a subproblem. Termination of the solution occurs once either the discrepancy between the upper and lower-level decision results meets a predetermined threshold or the maximum iteration count is attained. The output encompasses the results of decision variables, including factors such as RE output and the transmission capacity of subsystems.

RESs frequently encompass interconnected subsystems with interrelated and mutually dependent interests. For instance, problems such as GEP and TEP are formulated as upper and lower levels of BP (Jenabi et al., 2013). Similarly, models for both planning and operation (Zhang et al., 2016), as well as decisions in environmental and energy sectors (Chen et al., 2016), are considered. This extends to collaborations involving generation, transmission, distribution, and storage subsystems within the RES or even joint optimization with external factors such as the environmental and transportation sectors. In this context, BP captures the dynamic interaction process of decision-making.

For instance, Zhang et al. (2016) structured an integrated planning model for a power system supply system, using the upper level as a planning model and the lower level as a UC model. To optimize decisions related to distribution grid operation and DRG, Asensio et al. (2017) formulated the upper level with generation and grid investment constraints, influenced by the lower level's objective of minimizing payments for consumer participation in DR.

The bilevel MO optimization model encompasses two scenarios: Either a single level with multiple objectives or both levels having MOs. Shang et al. (2023) established a bilevel framework with three objectives: Maximizing net present value (NPV) benefits, minimizing annual carbon emissions, and minimizing energy conversion losses. This framework optimizes the size of the electricity-hydrogen system at the upper level and microgrid operations at the lower level. In another example, Matin et al. (2022) set upper-level objectives to minimize total costs and the System Average Interruption Frequency Index (SAIFI), and lower-level objectives aimed to optimize the daily operation strategy of the distribution system operator (DSO) by minimizing the deviation in reporting scheduling time and SAIFI.

4.2 MADM models

The MCDM approach, a subset of operations research, is employed to derive optimal outcomes in intricate scenarios involving diverse indicators and conflicting objectives and criteria (Kumar et al., 2017). This approach finds

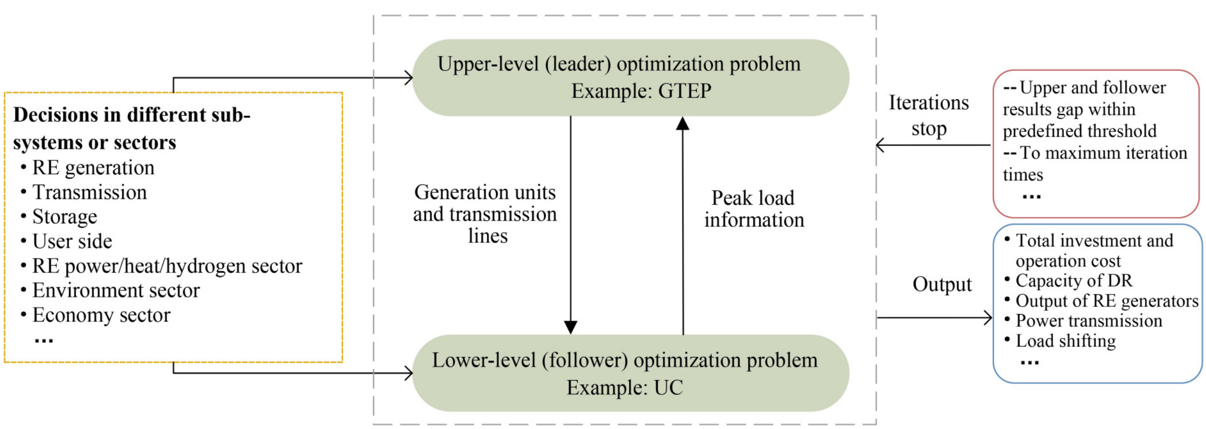

Fig. 10 Bilevel optimization models in RES.

extensive utility in addressing concerns such as the sequence of RE exploitation, the siting of power plants and facilities, energy planning, and the development of energy policies (Horasan and Kilic, 2022). The MCDM method can be categorized into two main categories: Multiobjective decision making (MODM) and MADM, as depicted in Fig. 11.

The previous section has already provided an overview of representative multiobjective optimization problems (MOPs) within the MODM framework. Another type is MADM, which is a model based on the MCDM approach with a finite decision space. While some studies directly employ MCDM, most make use of the MADM approach, which offers a suitable option for evaluating and comparing the characteristic properties of alternatives (Villacreses et al., 2017). This approach encompasses various techniques, including the weighted product model (WPM), the weighted sum model (WSM), the analytic hierarchy process (AHP), TOPSIS, fuzzy AHP/TOPSIS, and the elimination et choice translating reality (ELECTRE) (Mardani et al., 2017).

In research focused on assessing RE potential, optimizing site selection, and developing RE mechanisms, Salehin et al. (2016) considered factors such as financial investment, emission levels, local infrastructure, and durability in selecting technical and economic components for a PV-wind-diesel RE system on Kutubdia Island, Bangladesh. To determine the best power generation solution for Nigeria, Emovon and Samuel (2017) utilized the MADM approach to incorporate factors such as funding constraints, maintenance challenges, corruption, manpower shortages, military activities, and inappropriate siting. The MADM methodology was also applied to establish evaluation criteria for the state of RE development in China from energy, economic, technological, environmental, and social perspectives (Li et al., 2020a).

4.3 Game models

Game theory examines decision-making and equilibrium when the actions of decision-makers directly interact. It operates on the premise of the "rational man" hypothesis and is applied to oligopolistic economic markets. This model extends an individual's utility function from an indirect pricing system to a nonprice system, acknowledging that optimal choices are influenced by rationality and the strategies of others (Khare et al., 2016). Given that the energy industry often functions within an oligopoly market, game theory finds frequent application (Khare et al., 2016). In the context of RE, the term "player" pertains to entities such as power generation, transmission, and distribution companies, various energy and environment sectors, or local and central governments. The theory is categorized into noncooperative and cooperative games based on individual and collective rationality. Noncooperative games reach equilibrium when players cannot further increase profits by altering their individual strategies. In contrast, cooperative games involve the

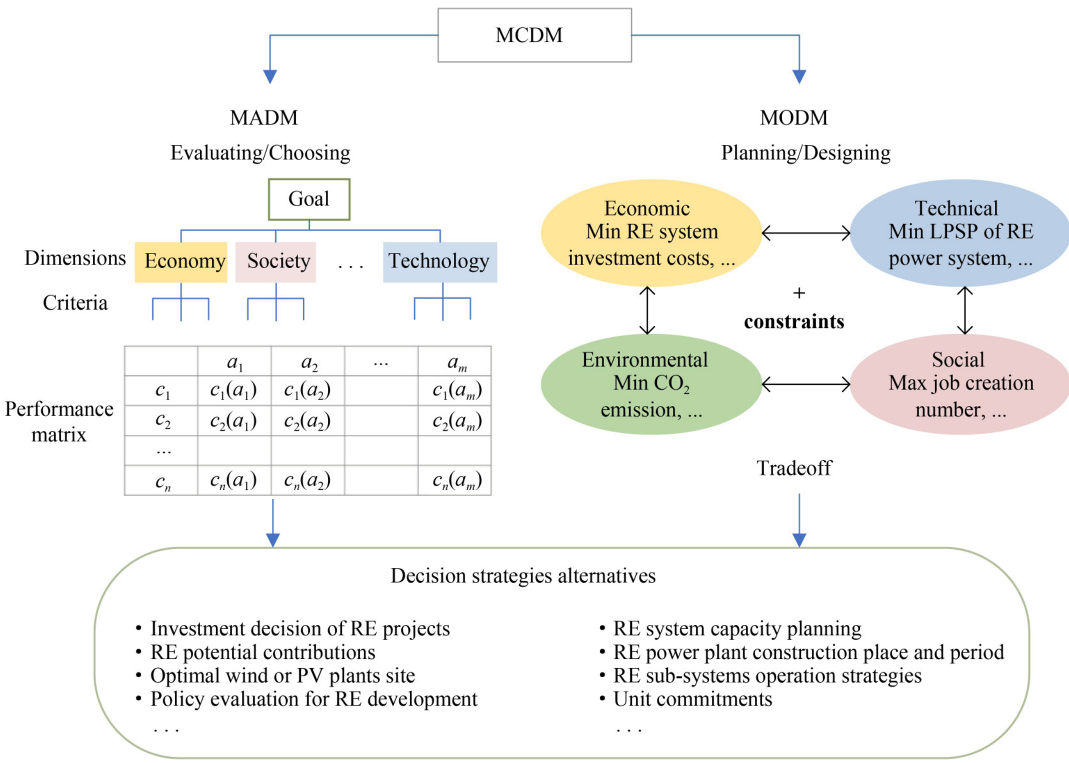

Fig. 11 MADM and MODM models in the RE system.

RES coalition aiming to maximize joint profits through binding agreements (Churkin et al., 2021). Figure 12 illustrates the game modeling involving players, decision objectives, and variables within the realm of RES.

The noncooperative game refers to a process where players make independent decisions, often resulting in a Nash equilibrium. Chuang et al. (2001) devised a Cournot model to depict expansion plans in the power generation industry, focusing on investment choices and market participation decisions. He et al. (2012) integrated cap-and-trade and carbon tax policies into a bilevel game GEP model, assessing policy effects on RE generation and grid companies' investment through Nash equilibrium. Ng et al. (2009)'s Cournot model of strategic interaction between power generation and transmission companies and Tao et al. (2021)'s bilevel game model involving thermal plants, RE plants, and power to gas (P2G) stations in an oligopolistic market present comparable noncooperative game models in RES.

The cooperative game model is increasingly applied in RES decision-making processes. Acuña et al. (2018) developed a bilevel model based on Stackelberg's duopoly cooperative game to address profit maximization and distribution between power generation companies and marketers. Additionally, Liu et al. (2021) formulated a cooperative game scheduling optimization model between MGs and distribution network operators, encompassing considerations for CCHP, heat pumps, and electrical and thermal energy storage.

While cooperative and noncooperative games provide static descriptions of energy market interactions, real markets are dynamic. The evolutionary game model emphasizes the dynamic equilibrium process within a group, departing from classic "rational man" and "complete information" assumptions and merging rational analysis with dynamic evolutionary processes. The primary assumption is that players will enhance their choices myopically based on imitation schemes (Sandholm, 2010). In RESs, evolutionary game models are often employed to address the strategic choices of governments, power generation companies, and users. For example, Dong et al. (2022) established a tripartite evolutionary game model involving regulators, RE companies, and grid companies, fostering policy synergy between FIT and RPS. To tackle grid-connected wind power curtailment, Coninx et al. (2018) devised an evolutionary game model involving flexibility providers and users. Jamali et al. (2022) established a one-population evolutionary game model involving manufacturers, power suppliers, and the government, exploring power purchase strategies in RES.

4.4 Hybrid models

A hybrid model, which complements theoretical or data-driven support for mechanisms within optimization models, offers enhanced applicability and validity. Such models often involve combining two or more existing models to create a new approach (e.g., an optimization-prediction hybrid model, a simulation-optimization model, etc.) to overcome limitations inherent in a single methodology or theory (Pan et al., 2018). In RES

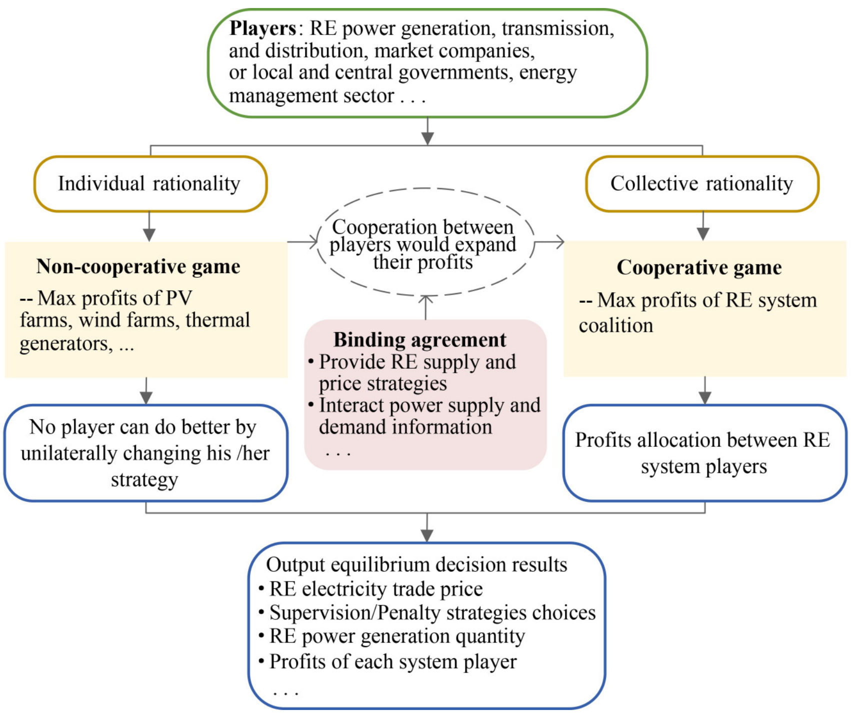

Fig. 12 Game models in RES.

modeling, frameworks incorporating probability analysis, simulation, LCA, cost–benefit analysis, and modern portfolio theory are commonly employed (Dagoumas and Koltsaklis, 2019). Among these approaches, prediction models typically provide crucial parameters such as RE power or heat demand, which serve as inputs for system simulation or optimization models to compute variable values such as RE capacity, electricity price, and demand or to explore causal relationships between variables. Furthermore, assessment models are often utilized to evaluate portfolio risk associated with RE power generation technologies and other related topics, as illustrated in Fig. 13. Soft-linking methods play a vital role in connecting these various components.

Prominent studies involving hybrid models for RESs, including system dynamics (SD) and mixed integer programming (MIP) models, have been combined to address RE power expansion plans in Portugal (Pereira and Saraiva, 2011) and Spain (Pereira and Saraiva, 2013) and the policy effects of FIT and RPS optimization by Dong et al. (2022) through the combination of an evolutionary game model and SD model. Curto et al. (2020) merged an LCA model, LCOE optimization model, and failure condition simulation to optimize the stability of an RES energy mix. Likewise, Hou et al. (2016) employed a nonlinear optimization model alongside a wind farm layout simulation for a decommissioning scheme. The layout planning for a wind power hydrogen manufacturing plant was determined by Olateju et al. (2016) through a fusion of the wind energy forecasting model, nonlinear optimization, and discounted cash flow evaluation model. Khanjarpanah et al. (2018) integrated a multiperiod optimization model with a double frontier network data envelopment analysis (DEA) model to assess efficiency and select suitable locations for HRESs in Iran.

Commonly used energy models such as LEAP, HOMER, and RETScreen are often integrated to form hybrid models. For instance, Kumar (2016) employed the LEAP energy model to simulate and optimize RE development and scheduling, predicting the impact of energy demand, consumption, and environmental emissions in Indonesia and Thailand under varying policy scenarios. Salehin et al. (2016) utilized the HOMER tool for optimizing the scale of RES on Kutubdia Island, Bangladesh, and combined it with the RETScreen energy assessment tool to conduct a comprehensive analysis of technical and financial feasibility (Liu et al., 2009). Similar hybrid models include MESSAGE-China (Liu et al., 2009), the System Advisor Model (Aly et al., 2019), and EnergyPLAN (Prina et al., 2019).

Various models are frequently combined, especially when long- and short-term models are integrated. Soft-linking is often employed to connect different models, enhancing the level of model detail. This approach utilizes varying temporal, technical, and spatial details to express two levels of resolution for the same or related problems, rather than directly increasing resolution or introducing additional equations for higher resolution (Deane et al., 2012). The execution of hybrid models occurs sequentially, allowing input from the latter model to be merged with output from another. Feedback loops between models can also aid in parameter or constraint adjustments, as seen in bidirectional soft links (Collins et al., 2017). For instance, Mimica et al. (2022) utilized soft-linking methods to enhance temporal resolution from 1 to 0.5 hour. Similarly, Deane et al. (2012) increased the

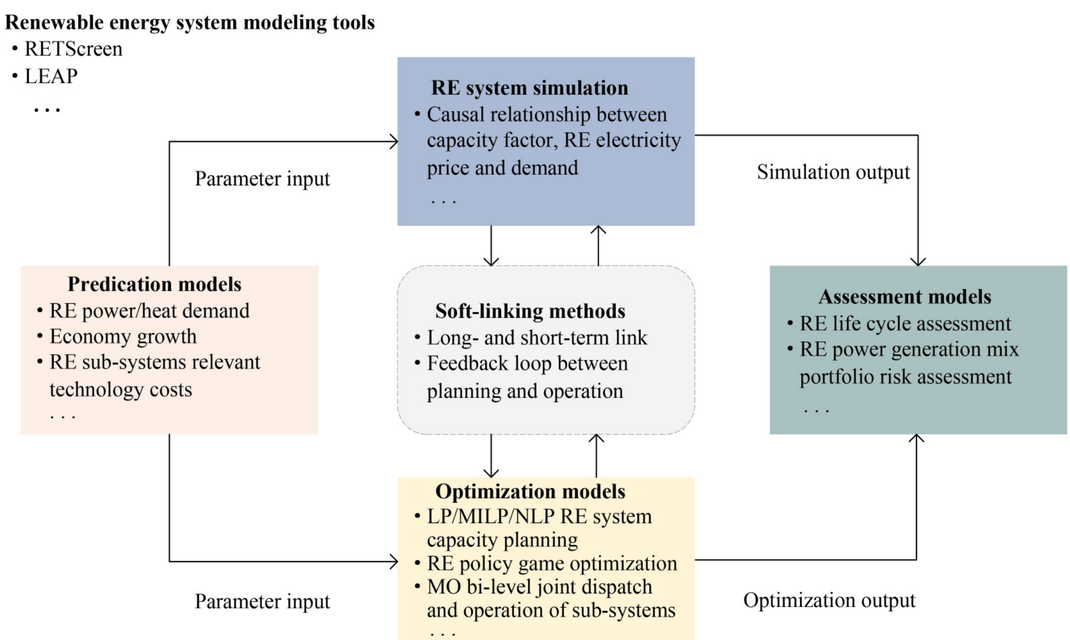

Fig. 13 Hybrid models and interrelationships in RES.

temporal resolution for renewable technology parameter analysis by conducting TIMES energy system optimization models with a target year of 2030, followed by connecting the output to the PLEXOS UC and economic dispatch model using a unidirectional soft-linking method.

Drawing from the review, a comparison of the advantages and disadvantages of the four models is presented in Table 3.

5 Solution methods for RES modeling

The solution methods for models developed by RESs can be categorized into conventional, probabilistic, artificial intelligence (AI), and hybrid approaches, as depicted in Fig. 14. Selecting a more efficient solution method requires careful consideration of model types and their characteristics.

5.1 Conventional methods

5.1.1 Analytical methods

The analytical method is a deterministic approach based on mathematical analysis and computational techniques. It involves performing repeated calculations or simulations using algebraic functions developed for the feasibility and convergence of the RE subsystem to obtain a set of feasible system configurations (Yang et al., 2020). By comparing the performance indicators of different configurations, the optimal system solution can be determined (Koltsaklis et al., 2014). Analytical methods encompass techniques such as simplex, gradient descent, and interior point methods, which are often integrated into commercial solvers.

Analytical methods involve iterative algorithms that perform recursion on the derivative of the objective function. The calculations continue until the optimal configuration is reached (Acuña et al., 2018). For instance, Memon et al. (2021) employed the generalized reduced gradient (GRG) method for nonlinear processing to solve a hybrid RES planning model. Ng et al. (2006; 2009) utilized the equivalent quadratic programming problem (QPP) with discrete constraints as additional constraints and employed an iterative search method to solve the independent GTEP Cournot model.

Commercial model solvers such as Lingo and CPLEX often include simplex techniques, interior point methods, and branch-and-bound methods for various applications (Sharan and Balasubramanian, 2012; Koltsaklis et al.,

Table 3 Comparison of different models

Models		Advantages	Limitations
Programming models	LP	·Most widely used in every corner of RES ·Have mature solvers	·Limited linear relation and expression ·Strictly rely on data accuracy
	NLP	·Iteration methods and lots of heuristic algorithms ·Optimal power flow question	·Local optimum ·Possible severe scarcity by means of linearization
	MILP	·Decision on integer results ·Help decide whether to do, e.g., RE facility location problem	·High requirements for algorithm accuracy ·Hard to solve large-scale models by an exact algorithm
	DP	·Widely used in optimization with risks and uncertainties ·Solve problems with multistage attribute	·Curse of dimensionality ·Large space requirement
	SP	·Uncertainty decisions in RESs ·Flexible and alternative models	·Difficult to analyze the running time ·Unknown probability of getting an incorrect solution
	BP	·Interaction between different decision-makers ·Suitable with different energy sectors or subsystems of RES	·Difficult to guarantee the optimal solution ·May only get the strong stationary solution
MCDM models	MODM	·Economic, technical, environmental, and social perspectives ·Suitable with conflicts in energy management and decision	·Hard to deal with inconsistent units among objectives ·Optimal Pareto fronts are hard to obtain
	MADM	·Evaluate the characteristic properties comprehensively ·Compare or rank for schemes	·Strong subjectivity to determine the weight ·Unable to provide new alternatives for decision-making
Games models	Noncooperative game	·Players make decisions independently	·Individual rationality ·Statistical decision and equilibrium process
	Cooperative game	·Profit maximization and distribution of RES	·Collective rationality ·Statistical decision and equilibrium process
	Evolutionary game	·Dynamic equilibrium process ·Relaxes “rational man” and “complete information” assumptions	·Evolutionary stable strategy derivation limitation ·Unable to characterize the uncertain decision
Hybrid models	With prediction/ simulation/assessment models	·Higher applicability and validity ·Complements theory for the optimization mechanism ·Data and result evaluation support	·Complexity of system and information exchange ·Difficult to link and balance different models

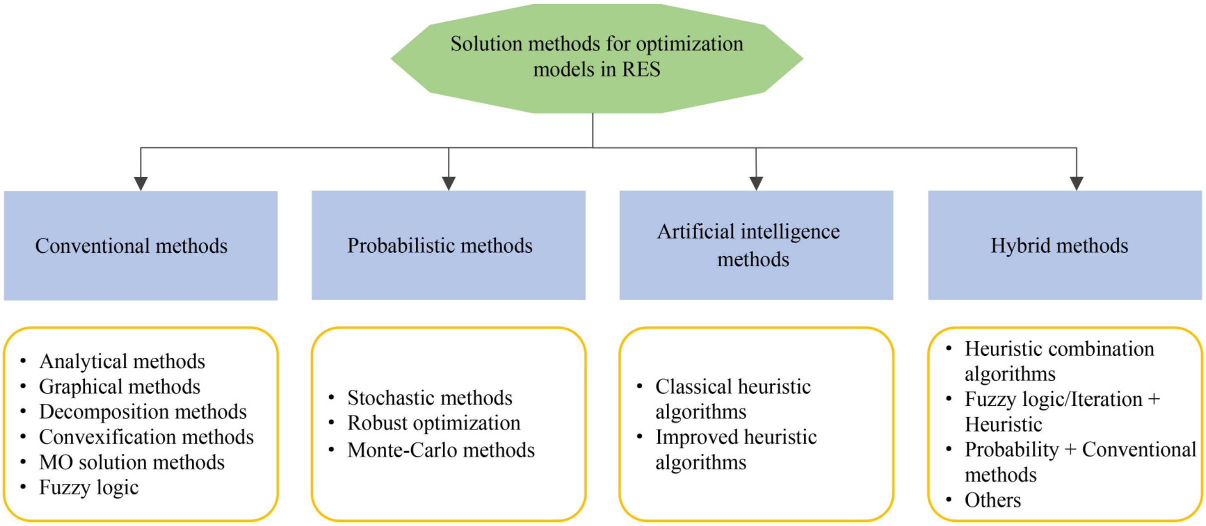

Fig. 14 Solution methods for the optimization model in RES.

2014). For instance, Arbabzadeh et al. (2019) used the CPLEX solver to address optimization models for energy storage technology deployment and operation strategies in California and Texas, USA. Tan et al. (2021) used Lingo to address the Xinjiang power dispatching nonlinear model in China with a 24-hour operation period under RPS price fluctuations. Chen et al. (2021) employed GAMS to solve a flexible GEP model integrating renewable power generation and consumer storage in Sichuan Province, China.

Nonlinear solvers are also popular for larger RES models and are available in platforms such as GAMS, including CONOPT (Yi et al., 2016), Bonmin (Zhang et al., 2016), and Gurobi (Xu et al., 2020). For example, Yi et al. (2016) utilized the CONOPT solver in GAMS to solve the bottom-up Chinese transmission planning model. Ahmadpour et al. (2021) applied the BARON solver to optimize the welfare impact of RE power planning and policy in a mixed integer nonlinear programming (MINLP) model.

The graphical construction method is employed to visually construct output curves using the average irradiance and wind speed of the RES. It also involves solving problems through calculus to determine tangent points (Amara et al., 2021). For instance, Markvart (1996) constructed the intersection of power supply and demand curves to determine the optimal configuration of two off-grid PV generators to meet energy demand, similar to the approach used in Borowy and Salameh (1996). However, this method disregards physical conditions such as the angle, height, or area of wind and solar modules and variations in BESS and load demand curves (Amara et al., 2021).

5.1.2 Decomposition methods

Decomposition methods are valuable for streamlining complex RES optimization models, particularly those involving high nonlinearity and dimensionality, especially in cases of long- and short-term optimizations across multiple subsystems. The concept of decomposition falls within the realm of indirect solution methods, aiming to reduce the computational burden associated with direct solution methods (Moradi-Sepahvand and Amraee, 2021a). Methods such as Benders decomposition and Dantzig-Wolfe decomposition involve breaking down the model problem into a master problem and subproblems (Flores-Quiroz et al., 2016; Zhuo et al., 2020). Zhuo et al. (2020) employed Benders decomposition to partition the master RE investment problem into multiple operational subproblems, thus enhancing efficiency and effectiveness. The approach has been used similarly to solve MILP models of RESs (Moradi-Sepahvand and Amraee, 2021a; 2021b; Li et al., 2022a). Moreover, Flores-Quiroz et al. (2016) utilized the Dantzig-Wolfe decomposition and column generation method to address the MILP model in the planning of the Chilean power system.

5.1.3 Convexification methods

Nonconvex optimization problems commonly encountered in RES, such as MIP and NLP, are often converted into extensively studied convex optimization problems (Neumann and Brown, 2021). Furthermore, Benders decomposition can be achieved through methods such as linearization substitution/approximation or specific relaxation conditions, which are widely employed for solving NLP and bilevel models. Relaxation, dual and elimination approaches, as well as penalty function methods, are typical strategies to transform problems into unconstrained optimization forms.

Solving NLP problems directly using standard algorithms can be challenging, prompting the use of linearization methods to transform the constrained problem into multiple unconstrained ones for solving. Methods such as the gradient method of calculus derivation and the Lagrange multiplier method are used for this purpose (Bertsekas, 1997). Fitiwi et al. (2016) utilized tangent or traversing linear inequality with an upper bound and piecewise linear approximation to solve the medium- and long-term TEP loss model. Brown et al. (2016) employed power transfer distribution factors to linearize and represent the Alternating Current (AC) load-flow equations. Peker et al. (2018) employed a Big-M type linearization technique to convert the problem into a solvable MILP model.

The BP model of RES is typically addressed by reducing the problem to a single level using techniques such as Karush–Kuhn–Tucker (KKT), duality, penalty function, and so on (Jenabi et al., 2013; Siddiqui et al., 2016), or by iterating a heuristic algorithm (Chen et al., 2016). To handle the nonlinearity involved, the original problem can be approximated as a quadratic problem using methods such as sequential quadratic programming (SQP) and further solved (Siddiqui et al., 2016), or it can be transformed into a linear form (Wu et al., 2018). For instance, Tao et al. (2021) used KKT to convert the condition into a single-level game payoff function, enabling the solution of the bilevel game model involving cooperation between the RE power plant and P2G station. Jenabi et al. (2013) utilized duality theory and KKT optimal conditions to formulate a mathematical program with equilibrium constraints (MPEC) for the bilevel Stackelberg game, subsequently simplifying the model to MINLP. Siddiqui et al. (2016) transformed the corresponding MPEC into an unconstrained NLP.

5.1.4 MO solution methods

MO solution methods that address conflicts within the RES can be categorized into various approaches, including priori methods (such as the single-objective transformation method (Gunantara, 2018), the ε-constraint method (Esmaili et al., 2011), and goal programming (GP) method (Bakhtavar et al., 2020)), interactive methods (such as the STEM method (Luz et al., 2018), weighted Tchebycheff method (Fan et al., 2020), and FL method (Yu et al., 2019)), and Pareto-dominated methods that use intelligent algorithms to directly obtain the optimal front (Tekiner et al., 2010) (as detailed in Section 5.3).

The priori method entails the decision maker providing sufficient preference information before initiating a one-time optimization process. The single-objective transformation method usually involves combining multiple objectives into one using various weighting techniques, which are then solved as a single-objective problem (Gunantara, 2018). Various objective weighting processes for MOPs include the simple weighted sum (Karaki et al., 2002), Grey-based weighting (Bakhtavar et al., 2020), distributed weights with steps (Yu et al., 2022), and proportion form to reduce objectives (Chen et al., 2015). The weighted sum method is a specific instance of the weighted metric method with an exponent set to one. Through this transformation, nondominated solutions are generated without relying on decision preference information.

The ε-constraint method involves determining the boundary ε for each objective function based on prior experience, designating one objective as the optimization target while considering the others as constraints (Tan et al., 2019). For example, Hu et al. (2019) modeled emissions as an emission-constrained cost using a carbon price floor, thus simplifying the dynamic economic emission scheduling model for traditional power plants and wind farms into a single cost objective. Similarly, when dealing with the economic and technical objectives of BESS operation, Weckesser et al. (2021) employed prior knowledge to establish reasonable ε-constraints.

In the goal programming approach, each objective function corresponds to an objective deviation, often categorized as positive and negative deviation variables. The problem is then transformed into minimizing these deviation objectives. For instance, Bakhtavar et al. (2020) utilized goal programming to transform MOPs related to energy mix optimization in net-zero energy communities, introducing undesirable deviation variables in objective functions. Zhuang and Hocine (2018) utilized meta-goal programming to address the de Novo programming problem in MODM for optimal planning of wind energy resource development. However, it is important to note that goal programming does not guarantee a Pareto-optimal solution.

Interactive methods involve the decision maker providing local preference information iteratively, modifying objective values gradually, and treating targets with reduced requirements as new constraints (Luz et al., 2018). For example, Luz et al. (2018) obtained an ideal solution set for an MO optimization model in GEP using the ε-constraint approach and then employed this ideal solution as a benchmark to estimate effective solutions. They subsequently identified objective functions that could be relaxed in each iteration, using the relaxed values to enhance other objectives. Fan et al. (2020) employed the weighted Tchebycheff method to solve the MO integrated distribution expansion planning problem.

Additionally, FL utilizes membership functions within the range of 0 to 1 to express the associated evaluation or priority of RES components in objectives (Su et al., 2000). For example, Yu et al. (2019) used fuzzy membership functions to handle the multidimensional objectives in RE development planning, effectively converting the model into a single-objective formulation. Waseem et al. (2021) proposed the Fuzzy Compromising (FCP) method to select the optimal solution from the Pareto front set, addressing the residential distributed power scheduling model.

5.2 Probabilistic methods

Probabilistic methods offer robust tools to handle uncertainty, encompassing the processing and resolution of uncertainty models and the establishment of PDFs or probability model generation along with parameter analysis. This approach can be realized through various techniques, including stochastic methods (Abdalla et al., 2019), which entail employing the expected value method and chance constraint method to transform models from stochastic to deterministic using mean values, probabilities, or simulations. Additionally, numerical methods such as the widely utilized Monte Carlo simulation (MCS) and Markov chain (MC) methods play a significant role (Tekiner et al., 2010).

Deterministic transformation solutions convert SP into equivalent deterministic programming by utilizing the PDFs of uncertain variables (Abdalla et al., 2019). The expected value method entails computing the mean probability of the random variables. For instance, Sun et al. (2018) proposed a method involving vine copulas for random scenario generation and expected value conversion to address random variables such as load, RE generation, and power transmission. This approach transformed the problem into deterministic programming. On the other hand, the chance constraints method addresses problems with random variables in the constraints, with decisions made prior to the realization of these random variables. This approach allows decisions to possibly deviate from constraints to a certain extent while ensuring that the probability of adhering to the established constraints is not lower than a confidence level α (Abdalla et al., 2019). As an example, Li et al. (2022b) introduced a distributed robust optimization chance constraint programming (DROCCP) method to resolve coordination challenges in RES.

Probability-based numerical methods, often referred to as scenario methods, involve generating a representative set of random variable samples. By attaining optimal performance across all scenarios, approximate solutions are achieved, which are particularly effective when dealing with uncertainties such as loads and external energy prices. Among these methods, MCS and MC are the most widely adopted (Abdalla et al., 2019). For instance, Tekiner et al. (2010) utilized MCS to generate system component state scenarios and subsequently solved the SP model for renewable power systems. Gbadamosi and Nwulu (2020) employed MC to assess the time-varying probabilities of renewable power system outage states, failure rates, and repair rates. They then solved the SP model concerning power generation and transmission system reliability.

5.3 Artificial intelligence methods

AI methods encompass intelligent computer programs that replicate or unveil natural phenomena or intelligent behavior observed in biological groups. These methods are grounded in scientific theories and engineering practices, offering a refined approach akin to the analytical method. They refine the search space with each iteration, leading to swift performance (Hannan et al., 2020) and solution flexibility that mitigates the risk of getting trapped in local optima. Notable among these methods are metaheuristic algorithms, exemplified by the GA, PSO, differential evolution (DE), and the nondominated sorting genetic algorithm (NSGA) (Hou et al., 2016; Salkuti and Kim, 2019; Namilakonda and Guduri, 2021). These algorithms generate individuals randomly, with populations guided by constraints. In addressing the extensive optimization required by RESs, traditional methods struggle to traverse the search space swiftly. AI methods exhibit versatile characteristics, are easily parallelizable (Hannan et al., 2020), and adeptly manage the nonlinear attributes of RES components, including the intermittent nature of RE resources (Su et al., 2018).

Original AI methods have found consistent application in the realm of RE. For instance, Sarker et al. (2019) employed GA to tackle a MINLP model for optimizing a biomethane gas production system's transportation network. Huy et al. (2020) harnessed a DE algorithm to address an MO model related to integrated distributed generation and distribution system planning. Haghighi et al. (2021) utilized PSO to resolve a GEP to achieve a Nash equilibrium between a government agent and power plants.

In response to the substantial computational burden imposed by nonlinearity in RES, researchers have introduced diverse AI improvement algorithms to enhance solutions. For instance, Namilakonda and Guduri (2021) introduced a modified Chaotic Darwinian Particle Swarm Optimization (CDPSO) to address a transmission congestion management model with nonlinear OPF. Hou et al. (2016) employed an adaptive PSO (APSO) algorithm to solve a wind farm decommissioning planning model with a life cycle cost objective.

Regarding MO optimization models in RES, heuristic AI algorithms such as NSGA-II, NSGA-III, and multiobjective PSO (MOPSO) frequently come into play to achieve the Pareto front (Hajebrahimi et al., 2017). For example, Hajebrahimi et al. (2017) applied NSGA-II to resolve a probabilistic MO model concerning smart grid expansion planning. He et al. (2021) employed NSGA-III to address a capacity optimization model for a combined storage-electricity-heat production system. Siddiqui and Dincer (2021) employed a multiobjective genetic algorithm (MOGA) to optimize the design of an HRES with hydrogen production. Sadeghi et al. (2020) utilized the MOPSO algorithm to solve an optimization model involving HRES with EVs. Ullah et al. (2021) proposed a multiobjective wind-driven optimization (MOWDO) algorithm and MOGA to address an operational optimization model for smart MGs.

ML algorithms are data-driven and require fewer system modeling details, making them adept at handling stochasticity (Musbah et al., 2022). These algorithms encompass techniques such as DL, NNs, and reinforcement learning (RL). Numerous studies have applied ML methods to solve RE-related optimization models. For instance, Xiong et al. (2018) utilized a single hidden layer neural network to fit the investment-benefit relationship of distribution networks, resolving an investment decision model. Narayanaswamy et al. (2023) introduced regularized deep neural network algorithms to optimize PV topology reconfiguration. Wang et al. (2020b) employed a stacked autoencoder (SAE) to evaluate the efficiency of distribution network asset utilization, solving a distribution network expansion planning model across multiple years. Remani et al. (2019) introduced an RL approach to address residential load scheduling in RESs. Zhang et al. (2019a) proposed deep reinforcement learning (DRL) to optimize wind energy operations in an integrated energy system. Similar studies have also emerged (Ye et al., 2020; Shao et al., 2021b; Li et al., 2023).

Furthermore, improved ML algorithms have surfaced in recent research, finding continued utility in the RE domain to accommodate growing problem dimensions and scenarios. These algorithms offer optimal solutions by selecting appropriate architectures, identifying network parameters, and adjusting learning rates according to real-time environmental conditions and uncertainties (Zhang et al., 2019b). Schulman et al. (2017) introduced proximal policy optimization (PPO) grounded in RL, offering multiple epochs of mini-batch updates of policy gradients compared to DRL. Zhang et al. (2021b) applied the PPO algorithm to train agents (power system operators) for optimal energy management strategies, solving an MO scheduling optimization model for distributed RESs. Zhou et al. (2020) devised distributed proximal policy optimization (DPPO) to address a CCHP system scheduling model, effectively responding to system emergencies.

5.4 Hybrid methods

A hybrid tool or algorithm, combining two or more of the methods mentioned above, can overcome the technical limitations inherent in a single approach and facilitate interactive information exchange across different levels or categories of the model (Neshat and Amin-Naseri, 2015). This encompasses the fusion of heuristic methods with FL, iterative or decomposition techniques within traditional methods (Samper et al., 2021), as well as the integration of multiple heuristic hybrid algorithms (Li et al., 2019).

Heuristic methods can strike a balance between accuracy and speed through amalgamating FL, iterative, decomposition, and probabilistic approaches (Samper et al., 2021). Combining FL with PSO, Li et al. (2019) addressed a collaborative planning model involving RE generation and energy storage within an active distribution network. Ding and Wei (2021) merged the NSGA-II algorithm with the interior point method to solve a bilevel optimization model for district energy planning and operation. Dufo-López et al. (2016) employed a hybrid approach of GA and MC simulation to tackle a stochastic model for an off-grid HRES power supply.

Various heuristic algorithms are integrated to enhance the solution efficiency of RE optimization models (Li et al., 2019). For example, Zhang et al. (2019b) resolved a wind-solar-hydrogen HRES scale optimization model for remote areas by blending chaotic search, harmony search, and simulated annealing into a novel algorithm, which demonstrated superior performance. Li et al. (2019) addressed nonlinear bilevel MO models using an NSGA-II-based enhanced PSO algorithm, facilitating collaborative planning between RE units and energy storage hierarchically. Salkuti and Kim (2019) introduced a two-objective congestion management optimization model, followed by the design of a multiobjective Glow-Worm Swarm Optimization (MOGSO) algorithm. To tackle a novel dynamic economic emission scheduling model, Hu et al. (2019) employed a hybrid approach of GA and SQP. Shakibi et al. (2023) resolved an MO optimization model for power and freshwater cogeneration involving solar and natural gas by combining DL algorithms, support vector regression (SVR) methods, and a multiobjective gray wolf optimizer (MOGWO). The integration of heuristic algorithms, especially for the nonlinear challenges in RES, accelerates the search for approximate solutions. Additionally, depending on the need for an exact solution and the level of satisfaction needed, such hybrid approaches can significantly reduce the computational cost of finding solutions (Twaha and Ramli, 2018). Hybrid algorithms incorporating emerging AI techniques demonstrate robust calculations, improved convergence, and enhanced accuracy (Afzal et al., 2023).

Drawing from the aforementioned insights, a comparison of the advantages and disadvantages of the four methods is presented in Table 4.

6 Summary of future trends

6.1 Trends regarding optimization modeling in RES

Based on the comprehensive literature analysis presented in the preceding sections, the following trends pertaining to optimization modeling of RESs have been identified.

(1) Substituting deterministic models, uncertainty models are poised to assume prominence. Driven by the inherent attributes of RE resources, forthcoming RES optimization modeling endeavors will exhibit heightened parameter uncertainties. Examples of such uncertainties

Table 4 Comparison of different types of solution methods

Methods	Advantages	Drawbacks
Conventional methods	·Mathematic simplify methods ·Flexibility with models ·Enable mechanistic analysis	·Limited space and speed ·Rely on commercial software or numerical approximations ·Require explicit mathematical formulation
Probabilistic methods	·Eliminate the need for time-series data ·Overcome restriction of limited data ·Uncertainty consideration of subsystems	·Difficult to represent dynamics of systems ·Vast resource data ·Need accurate historical data
Artificial intelligence methods	·High convergence speed ·Accurate prediction ·Variable and Bionic algorithm ·Strong robustness and noise immunity	·Rely on data amount and hardware facility ·Difficult to find suitable models ·Internal black box lacks mechanistic explanation
Hybrid methods	·Balance between local and global exploration ·Improved searching capability and accuracy ·Most robustness	·Complexity of system and information exchange ·Difficult to balance different methods and design codes

encompass volatile oil, electricity, and carbon prices, prognostications for electricity and heat load values, surveillance of RES system failure or condition in smart grids, and fluctuations in electricity supply and demand attributed to EVs' integration with the grid. Within the framework of uncertainty models, methods of data-driven parameter identification and prediction are listed.

(2) Models featuring comprehensive energy carriers can leverage soft-linking techniques to encapsulate interactions between the renewable power system and other energy systems or sectors. These interactions encompass the exchange of information regarding energy quantities, prices, water cycles, and similar aspects. Moreover, attention must be directed toward considering the technical attributes of electricity, heat, and gas networks. Addressing the multifaceted challenges of multiscale and multitimescale synchronization is imperative, particularly in the context of confronting dynamic uncertainty in multienergy systems.

(3) Elevation in spatiotemporal resolution modeling and the employment of time series aggregation techniques, exemplified by the representation of days or periods, are poised to gain ascendancy. This entails adopting a finer temporal resolution, such as 15 minutes, along with an extended time horizon, reaching up to a year. Beyond national and regional contexts, specific locales such as islands and remote regions have garnered augmented interest due to distributed generation. Consequently, research has been refined to encompass power plants and even individual units. Notably, studies pertaining to DRG incorporate ML models to bolster decision optimization due to the extensive scope of UC and OPF challenges.

(4) The integration of advanced simulation programs within the modeling framework is projected. This integration encompasses intricate aspects of intermittent systems with high penetration of RE sources, capturing real-time conditions and intricate details. Instances include short-term DR within smart grids, power plant decommissioning, energy storage operation, and instances of extreme weather and events. Timely feedback is provided, accompanied by insights into simulation and optimization findings. Additionally, the techno-economic performance evaluation, along with an assessment of user-perceived value of RES, is furnished.

(5) A pivotal trajectory for RES modeling lies in AI-based generative models. Specifically, generative models rooted in AI emerge as a critical avenue. By way of illustration, the production of high-quality scenarios pertinent to RE is facilitated by training and distinguishing samples utilizing generative and discriminative models embedded within the generative adversarial network framework. These generative models serve to predict RE output, energy prices, and similar variables. This augments the representation of volatility and uncertainty, subsequently enhancing the operational and scheduling optimization models for RES. Integrating the generative model with the optimization framework introduces AI's predictive capacity, effectively amalgamating historical data and static models with the intricate constraints, MO criteria, and distinctive attributes inherent to the optimization model, ultimately enhancing the accuracy of optimization decisions.

6.2 Trends regarding solution methods for optimization models in RES

The scope of RES modeling and the requisite computational memory are poised to expand. As such, forthcoming endeavors warrant an exploration of algorithmic facets, encompassing the following dimensions.

(1) Consideration should be given to the amalgamation of analytical and heuristic methods to enhance solution efficiency. This amalgamation could entail the fusion of heuristic algorithms to approximate solutions, particularly when addressing nonlinear RES problems. Subsequently, the determination of the necessity for an exact solution can be made.

(2) A deeper investigation into approximation techniques, including linearization and relaxation, is imperative. In instances where intricate models entail nonlinear, high-dimensional power flow equations and

thermodynamic constraints, simplification or convexification can be harnessed. This facilitates equivalent transformations or the establishment of more succinct and appropriate linear relationships.

(3) The application of AI-based optimization algorithms rooted in DL or reinforcement learning is an avenue to explore within the realm of RE. Notably, techniques such as DRL, the model-free DRL approach, PPO, DPPO, and multiobjective PPO hold potential. This is particularly pertinent in expediting RES configuration planning and optimizing operations, encompassing renewable power generation or load prediction. While ML methodologies have witnessed a surge in research activities, their application in the RE domain remains relatively constrained. Future endeavors should be directed toward automatic parameter adjustment within optimization algorithms, devising operational strategies through simulations of smart grids, the Energy Internet of Things, and the maintenance and fault detection of RESs. Despite the considerable demand for data and prolonged parameter training, progress in this realm stands to significantly influence solution performance.

7 Conclusions

Based on the comprehensive examination of the REDUC process, this review segment delineated the RES into five distinct subsystems, subsequently summarizing the spectrum of optimization models and corresponding solution methodologies. The ensuing conclusions are as follows.

(1) Optimization within the ambit of RE systems is oriented toward addressing decision quandaries encompassing investment, construction, operation, maintenance, and dispatch. Within the exploitation and production subsystem, optimization endeavors center around devising plans for power plant investment and construction. Emphasis in the power transmission and distribution subsystem pertains to optimizing grid layout investments and fostering collaborative operations. In the consumption subsystem, paramount consideration is accorded to ensuring secure dispatch and equitable alignment of interests among all stakeholders. Explorations in the energy storage subsystem predominantly revolve around distinct investment scale configurations for energy storage systems, coupled with charging and discharging strategies.

(2) The prevailing paradigm for current RES decision-making optimization prominently revolves around the amalgamation of theories and methodologies culled from diverse domains, including prediction, optimization, simulation, and assessment. These hybrid models predominantly amalgamate principles from power engineering, environmental science, and computer science. Moreover, they incorporate elements of uncertainty, human factors, and dynamic attributes. Predictions and simulations often serve to calibrate parameters during the modeling process. Furthermore, optimization decisions are frequently conjoined with models such as LCAs, techno-economic assessments, and cost–benefit analyses.

(3) The prevailing solution framework for extensive RES configurations necessitates an amalgam of model decomposition, linearization techniques, hybrid analytical approaches, and AI algorithms. Addressing the intricate task of coupling optimization across multiple subsystems entails substantial computational burdens. Conventional direct solutions and iterative techniques exhibit sluggishness in their convergence. Consequently, strategies of simplification, typified by linearization or relaxation, are commonly employed to navigate the complexities of intricate models. This, when harmonized with traditional analytical methods and AI algorithms, augments the efficacy of solutions by streamlining computational demands.

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