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A comprehensive review of optimum integration of photovoltaic-based energy systems

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ABSTRACT

The economic viability of solar power has led to widespread adoption in homes and businesses. However, its intermittent nature requires integration with other renewables and storage solutions to achieve peak efficiency. This study delves into the in-depth review and analysis of mathematical modeling for determining the optimum capacity of solar power plants and their combination with the other sources based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method. The main contributions of this research include a) Presenting the most commonly used variables for optimizing PV-based combination sources in the literature. b) Utilizing text mining on a large database in addition to the PRISMA model to increase the comprehensiveness of the results. c) Presenting all the common objective models in the literature, and d) Conducting a comprehensive comparison of solving techniques. This research provides valuable insights into the status and development trends in optimal sizing for PV energy systems by providing future direction in the renewable sources combination area.

Nomenclature and abbreviations

P_h	**Battery capacity (kWh)**	JA	**Jaya Algorithm**
$P_{b,im}$	Power import of the battery (kW)	LCC	Life Cycle Cost
$P_{b,ex}$	Power Export of the battery kW)	LCOE	Levelized Cost of Energy
$P_{b,in}$	Available input power of the battery (kW)	LHC	Levelized Hydrogen Cost
$P_{b,out}$	The Available output power of the battery (kW)	LOEE	Loss of Energy Expected
P_e	Power export limitation (kW)	LOLE	Loss of Load Expected
P_p	Power generation of the photovoltaic unit	LOLP	Loss of Load Probability
P_g	Total generated power (kW)	LP	Linear Programming
P_d	Demand Power (kW)	LPSP	Loss of Power Supply Probability
P_x	Curtailed Power (kW)	MBA	Mine Blast Algorithm
P_{im}	Power imported from the grid (kW)	MCS	Monte Carlo Simulation
P_{ex}	Power Exported to the grid (kW)	MDE	Multi-Objective Differential Evolution
P_w	Power generation of the wind turbine	MGWO	Multi-Objective Grey Wolf Algorithm
ABC	Artificial Bee Colony	MILP	Mixed Integer Linear Programming

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ACO	Ant Colony Optimization	MINLP	Mixed Integer Nonlinear Programming
ACS	Total Annual Cost	MLUCA	Multi-Objective Line-Up Competition Algorithm
AEFA	Artificial Electric Field Algorithm	MOP	Multi-Objective Optimization
AEO	Artificial Ecosystem Optimization	MPSO	Multi-Objective PSO
ALO	Antlion Optimizer	MSSA	Mult-objective Salp-Swarm Algorithm
ANN	Artificial Neural Network	NB	Number of Battery
BAT	Bat Algorithm	NM	Nelder-Mead Algorithm
BBO	Biogeography-Based Optimization	NPC	Net Present Cost
CE	Carbon Emission	NPO	Nomadic People Optimizer
COA	Coyote Optimization Algorithm	PC	Purchase Cost from Grid
COE	Cost of Energy	PL	Power Loss
CS	Cuckoo Search	PP	Payback Period
CSO	Crow Search Algorithm	PSO	Particle Swarm Optimization
DA	Deterministic Algorithm	PV	Photovoltaic
DE	Differential Evolution	RE	Revenue
DEE	Curtailed/Excess Energy	RF	Renewable Fraction
DG	Diesel Generator	RI	Reliability Index

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DP	Dynamic Programming	ROI	Return On Investment
EE	Embodied Energy	SA	Simulated Annealing
ES	Energy Storage	SO	Stochastic Optimization
FA	Firefly Algorithm	SOA	Seagull Optimization Algorithm
FC	Fuel Consumption	SSO	Social Spider Optimizer
FFO	Fruit Fly Optimization	TAC	Total Annual Cost
FPO	Flower Pollination Algorithm	TCC	Total Capital Cost
GA	Genetic Algorithm	TLBO	Teaching Learning-Based Optimization
GEI	Grid Electricity Import	TS	Tabu Search
GWO	Grey Wolf Algorithm	UL	Unmet Load
HOMER	Hybrid Optimization Multiple Energy Resources	VD	Voltage Deviation
HS	Harmonic Search	WOA	Whale Optimization Algorithm
ICA	Inspired Coevolutionary Algorithm	WT	Wind Turbine

1. Introduction

For many decades, the majority of electricity generation relied on fossil fuels. However, various factors have led to a global energy crisis and exacerbated environmental issues [1]. Renewable energy sources have become increasingly popular in recent years due to concerns about climate change, the environmental impact of conventional energy sources, and the diminishing availability of fossil fuel [2]. As illustrated in Fig. 1, the share of renewable sources in newly installed power plants worldwide has increased from 15 % in 2002 to 83 % in 2022, and their share of the total installed capacity globally is now approximately 40 % [3].

Among all renewable sources, solar-related sources have been the most widely adopted in recent years. Fig. 2 illustrates the total installed capacity of renewable sources between 2013 and 2022, as well as newly installed energy sources in 2022 by different technologies. Based on these results, more than 60 % of the newly installed capacity of renewable sources of energy in 2022 was from Photovoltaic (PV) systems [4].

Residential rooftop PV systems are increasing due to decreases in installation costs and government incentives [5,6], to the extent that the PV penetration rate in detached residential housing in some Australian states has reached 46 % in 2023 (Fig. 3). Fig. 3 shows that Australian households have tended to invest more in larger PV systems in recent years compared to previously.

The increase in PV penetration rate offers several advantages to both households and society, as it does not directly produce greenhouse gases or other harmful pollutants, thereby reducing the negative impact on the environment and public health [7]. In addition to its environmental benefits, PV contributes to energy security by enabling localized and distributed power generation, which reduces reliance on remote or foreign energy sources [8–10]. The growing use of renewable sources has also led to the creation of new jobs in manufacturing, installation, and maintenance, boosting local economies [1,11]. Another significant benefit of PV technology is its potential to improve energy access. PV systems can provide electricity and modern energy services to communities that lack access to centralized grid infrastructure. This improved energy access can yield extensive socioeconomic benefits, empowering communities and fostering their development [12–14].

Besides the mentioned advantages, PV comes with some disadvantages. As the output of PV-based plants is dependent on weather conditions, it exhibits high fluctuations, making them inconsistent and unreliable [15]. Furthermore, large-scale PV installations require significant amounts of land, which can lead to conflicts with other land uses, such as agriculture and conservation [1].

Due to the fluctuation in PV output, it is impossible to balance energy demand and supply with PV plants alone [3]. Therefore, combining PV with other generation sources, such as Wind Turbines (WT) and diesel generated energy is proposed in the literature. Besides generation plants, energy storage systems must be used to enhance the reliability of these systems [1].

Numerous models are presented in the literature to determine the optimum combination of PV with other generation and storage sources. Fig. 4, presents results from a search in Scopus using search terms "Optim* AND PV AND (Siz* OR Hybrid OR Combin*) AND (Battery OR Storage OR Wind OR Diesel)" indicating the increasing research in this area.

2. Methodology

A comprehensive review was conducted on the optimization of combined renewable energy sources based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method presented in Fig. 5 [16]. The PRISMA method comprises four stages: Identification, Screening, Eligibility, and Inclusion. In the first step, by searching keywords in the titles, abstracts, and keywords of articles in Scopus and Web of Science 8537 and 7774 articles were selected, respectively. Further refinement was made by searching titles only, which narrowed the records to 619 in Scopus and 449 in Web of Science. Filtering by the year of publication (post-2010) resulted in 585 records from Scopus and 422 from Web of Science. The document type was then restricted to articles, and the language filter was set to English, resulting in leaving 294 articles from Scopus and 248 from Web of Science. An

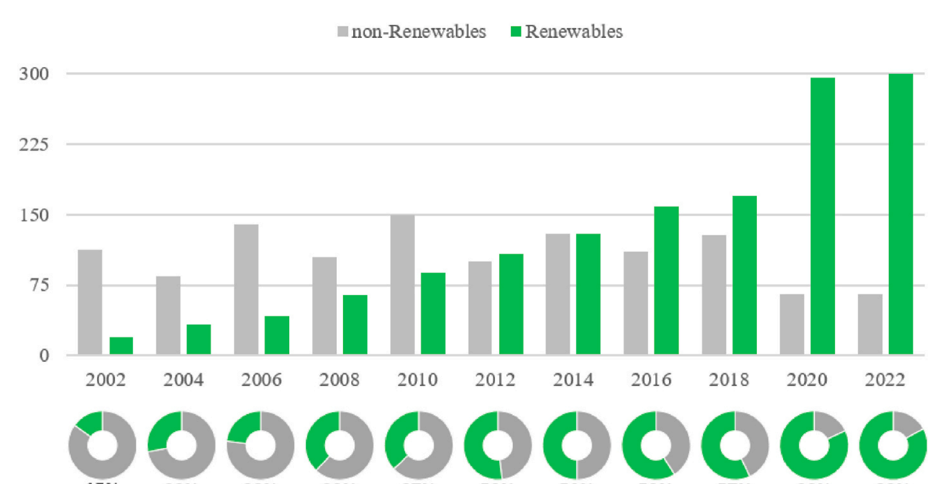
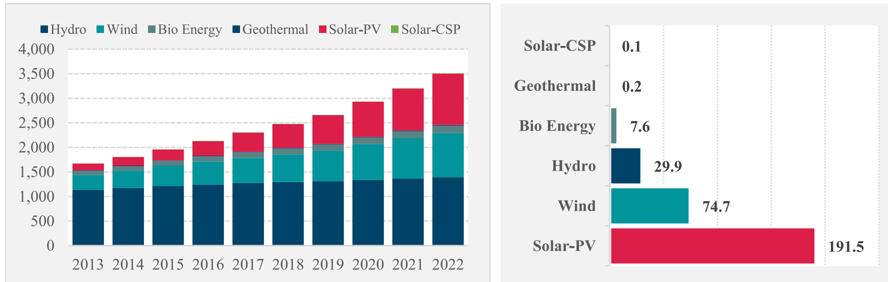
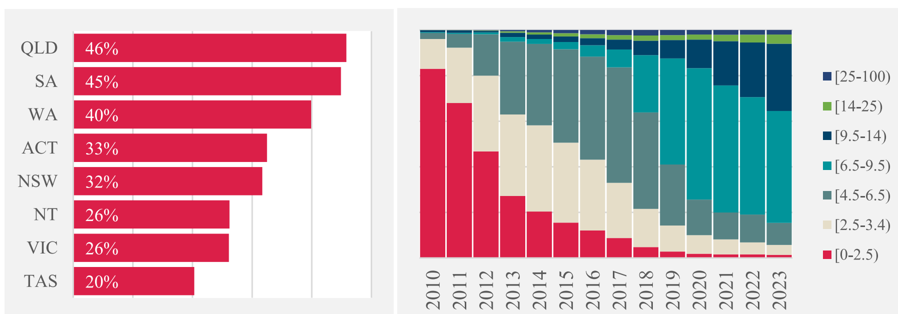


Fig. 1. Annual power capacity expansion, 2002–2022 [3].



a. Total capacity (GW)	b. New Installed Capacity (GW) in 2022

Fig. 2. Total and Newly Installed Capacity (in GW) of Renewable Energy Sources in 2022 around the world [4].



a) PV penetration Rate in the Australian	b) Distribution of rooftop PV sizes

Fig. 3. PV rooftop penetration statistics in Australia.

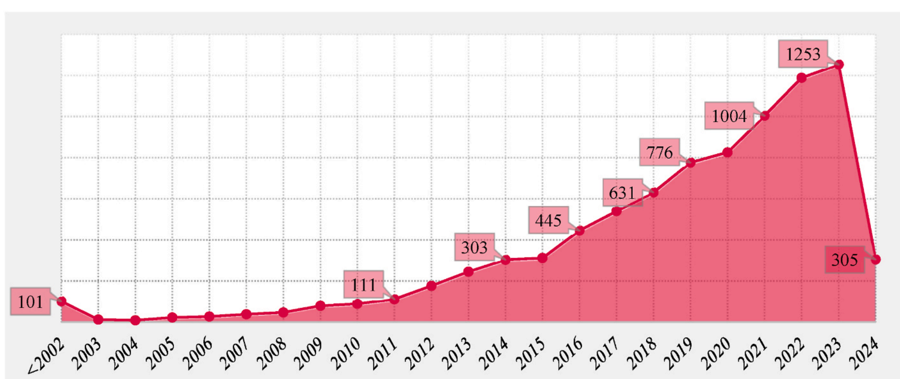


Fig. 4. Number of publications on the combination of PV with other sources between 2002 and 2023.

additional 61 articles were selected using the snowball approach via ConnectedPapers.com. After removing duplicate articles, the total number of unique records was 375. Titles and abstracts were then screened, further narrowing the pool to 183 records. Of these, 114 articles were selected after reading them fully. These 114 articles, summarized in Table 1, were used in this research for statistical analysis. To validate these results, they were compared with the outcomes of text mining for all 375 articles extracted at the end of the identification stage.

Fig. 6 presents the publishers of selected articles. Energy journals have a significant presence, with "Energy" leading at 13 papers, followed by "Renewable Energy" with 12, and "Solar Energy" with 10 papers. The most cited papers are presented in Fig. 7, publications in the dataset have been cited a total of 13,440 times, with an average citation rate of 114 citations per paper. The highest-cited paper, by ZHOU W. in 2010, has been cited 741 times, significantly more than the average citation rate of 114 per paper [17].

The output of PV system fluctuates significantly during the day due to their strong dependence on solar geometry and meteorological factors [18]. Additionally, the absence of PV generation at night makes it challenging to balance energy consumption and generation using PV alone. To address these limitations and create a sustainable energy generation system that meets demand, PV is often combined with other energy sources and storage technologies. Numerous models have been proposed in previous research to determine the best combination for different countries. Fig. 8 illustrates the distribution of these articles across countries. Thirty four countries were included, with Iran being the most studied country with 18 articles, followed by China and India, each with 9 articles. Regarding the type of grid connection, Fig. 9 shows the proportions of grid-connected and off-grid scenarios discussed in the articles. The findings suggest that the optimal combination of energy facilities is primarily determined for stand-alone systems. Four articles evaluate both grid-connected and off-grid scenarios to compare their

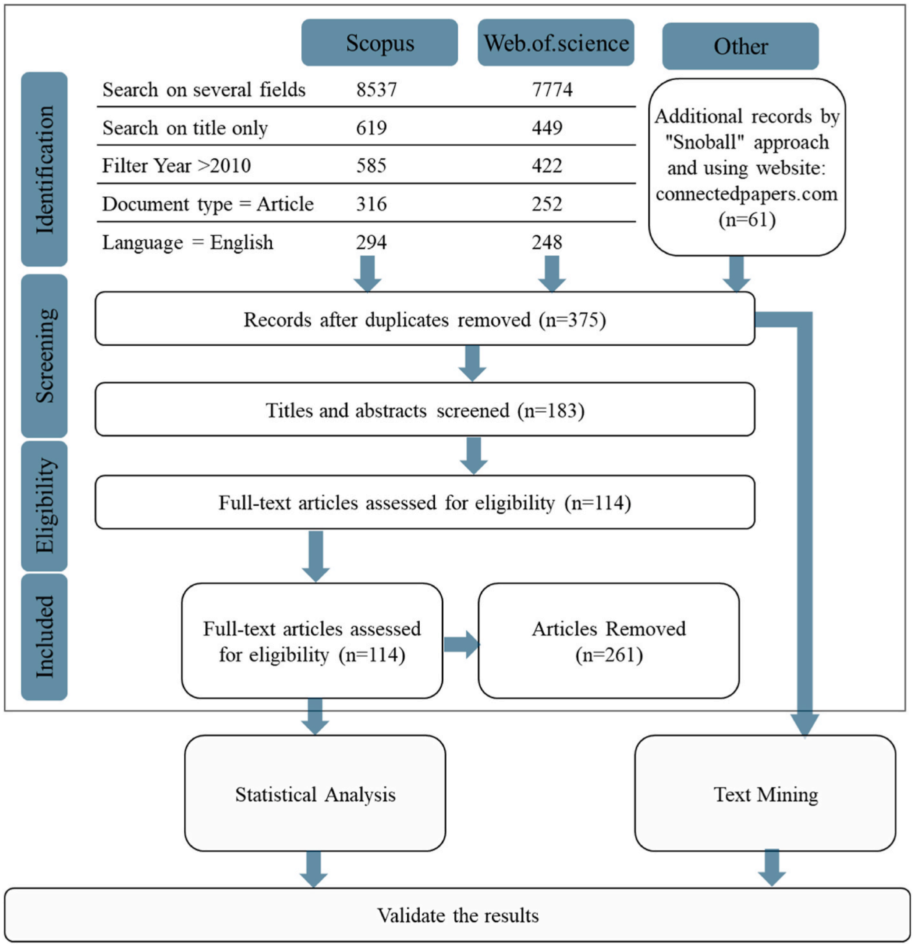


Fig. 5. Research flowchart.

outcomes including [19–22]. In the case of stand-alone systems, optimization is mainly conducted for microgrids, while for grid-connected scenarios, optimal sizing is most often assessed for residential buildings.

From another perspective, Fig. 10 presents the proportion of case studies in the articles. While almost half of the studies focus on microgrid cases such as islands, villages, or rural areas, 38 % of the articles determined the optimum combination of sources for buildings including residential, commercial, and offices. Additionally, 5 % of articles consider the demand for universities and campus areas. The remaining 9 % aimed to determine the optimum combination of sources for other cases such as farms, police stations, and ships.

The selection of a subset of articles may lead to potential errors and biased results, with some criteria possibly being omitted from the evaluation process. Although it is not feasible to address every concept, criterion, and assumption within this context, efforts have been made to minimize the risk of bias. To mitigate this risk, text mining was performed on a large number of articles. This approach ensures a more comprehensive evaluation by incorporating a broader range of information, thereby reducing the likelihood of missing critical criteria and assumptions.

To evaluate and encompass all key concepts in optimizing the combination of energy sources and reduce potential error, the essential criteria were first extracted from the selected articles. Subsequently, a text mining model was applied to a broad collection of articles to verify these criteria, ensuring comprehensive coverage of the main concepts in the optimal source combination. The text-mining procedure is illustrated in Fig. 11.

This approach begins with extracting primary keywords from abstracts, keywords, and titles of the articles. A word cloud is then created based on the frequency of these words. Next, a list of abbreviations, acronyms, and variant spellings of relevant concepts (such as "stand-alone" and "off-grid") is compiled and consolidated according to the review's perspective. The refined dataset is then used to generate the word cloud. The cleaning and verification process is conducted iteratively to ensure the thoroughness and accuracy of the dataset.

Figs. 12 and 13 present the results of the text mining process as a word cloud and word map depicting the most commonly used terminologies in related papers.

Based on the review and text-mining results, a range of criteria for comparing the articles, as presented in Fig. 14, was extracted. These criteria include the grid connection type, including grid-connected (on-grid), off-grid (stand-alone), or both. The decision variable, based on the combination of facilities, can vary among options such as PV/ES, PV/ES/DG, PV/WT/ES, etc. Storage types are categorized into chemical, electrochemical, mechanical, and thermal. Case studies cover microgrids on islands or rural areas, residential and non-residential buildings, campuses, universities, and other entities such as farms or police stations. Another criterion for comparison is the objective function encompassing economic, reliability, environmental, technical, and social aspects, as well as their combinations. Besides these criteria, solving techniques are categorized into five groups: traditional models, single heuristic algorithms, combined heuristic algorithms, software-based methods, and hybrid models. Detailed information about the selected papers is presented in Table 1. However, the focus of this research, as detailed in Fig. 15, is limited to the mathematical models, including decision variables, objective functions, model parameters and assumptions, and solution techniques. The main contribution of this study is providing an in-depth review of the mathematical models (including

Table 1
Details of reviewed articles.

Row	Reference	Year	Type of Solving Techniques	Solving Techniques	Combination Type	Type of Objective function	Objective function	Country	Location	Grid Connection
1	[23]	2015	Software Based	HOMER	PV/ES/DG	Economic	LCOE		Campus & Institution	stand-alone
2	[24]	2016	Single Heuristic Algorithm	PSO	PV/ES/DG	Economic + Reliability + Environmental	TAC + LOLP + CE	Algeria	Microgrid	stand-alone
3	[25]	2020	Single Heuristic Algorithm	MPSO	PV/WT/ES	Economic	TCC	China	Microgrid	stand-alone
4	[26]	2019	Software Based	HOMER	PV/WT/ES/DG	Economic + Environmental	NPC + CE	Ethiopia	Microgrid	stand-alone
5	[27]	2019	Single Heuristic Algorithm	FA	PV/WT/ES	Economic	COE	India	Microgrid	stand-alone
6	[28]	2018	Single Heuristic Algorithm	CS	PV/WT/ES	Economic	NPC		Microgrid	stand-alone
7	[29]	2019	Software Based	HOMER	PV/ES/DG	Economic + Environmental	NPC + COE + CE	Buildings		
8	[30]	2021	Single Heuristic Algorithm	PSO	PV/WT/ES	Economic + Technical	COE + RF	Algeria	Buildings	stand-alone
9	[31]	2020	Traditional Methods	MILP	PV/ES	Economic	TAC + ROI	Australia		
10	[32]	2019	Single Heuristic Algorithm	GA	PV/ES	Economic	TAC	Australia	Buildings	Grid-connected
11	[33]	2015	Combined Heuristic Algorithm	NSGA-II + MPSO	PV/ES/DG	Environmental	CE	China	Other	stand-alone
12	[34]	2020	Combined Heuristic Algorithm	JA + TLBO	PV/WT/ES	Economic	TAC	Iran		stand-alone
13	[35]	2019	Combined Heuristic Algorithm	CS + HS + SA	PV/WT/ES	Economic	LCC	Iran	Microgrid	stand-alone
14	[36]	2016	Single Heuristic Algorithm	GWO	PV/WT/ES	Economic	TAC	Iran		stand-alone
15	[37]	2014	Single Heuristic Algorithm	HS	PV/WT/ES/DG	Economic	TAC	Iran	Microgrid	stand-alone
16	[38]	2015	Single Heuristic Algorithm	ICA	PV/WT/ES/DG	Reliability + Economic	LPSP + ACS	China		stand-alone
17	[39]	2016	Hybrid Models	PSO + MCS	PV/WT/ES	Economic	TAC	Iran		stand-alone
18	[40]	2015	Single Heuristic Algorithm	PSO	PV/WT/ES	Economic	TAC	Iran	Buildings	stand-alone
19	[41]	2013	Combined Heuristic Algorithm	CS + HS + SA	PV/WT/ES	Economic	TAC	USA		stand-alone
20	[42]	2014	Single Heuristic Algorithm	ABC	PV/WT/ES	Reliability + Economic	LPSP + TAC	Iran		stand-alone
21	[43]	2017	Combined Heuristic Algorithm	NSGA-II + MPSO	PV/WT/ES	Reliability + Economic	LPSP + LCC	China		stand-alone
22	[44]	2014	Combined Heuristic Algorithm	PSO + SA	PV/WT/ES	Economic	LCC	China		stand-alone
23	[45]	2018	Combined Heuristic Algorithm	CS + NM	PV/ES	Reliability	PL	India		stand-alone
24	[46]	2015	Single Heuristic Algorithm	ACO	PV/WT/ES	Economic	NPC	Iran		stand-alone
25	[47]	2017	Single Heuristic Algorithm	MLUCA	PV/WT/ES/DG	Economic + Environmental	TAC + CE	China		stand-alone
26	[48]	2010	Single Heuristic Algorithm	SA	PV/WT/ES	Economic	TAC	Turkey	Campus & Institution	stand-alone
27	[49]	2012	Combined Heuristic Algorithm	SA + TS	PV/WT/ES/DG	Economic	LCOE	Greece	Buildings	stand-alone
28	[50]	2020	Combined Heuristic Algorithm	HS + SA	PV/ES/DG	Economic	LCC	Iran	Microgrid	stand-alone
29	[51]	2015	Combined Heuristic Algorithm	SA + FPO	PV/WT/ES	Reliability + Economic	LPSP + TAC	Iran		stand-alone
30	[52]	2010	Single Heuristic Algorithm	NSGA-II	PV/WT/ES	Economic + Reliability	ACS + LPSP	Senegal		stand-alone
31	[53]	2012	Single Heuristic Algorithm	GA	PV/WT/ES	Reliability	LOLP	Malaysia		stand-alone

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Table 1 (*continued*)

Row	Reference	Year	Type of Solving Techniques	Solving Techniques	Combination Type	Type of Objective function	Objective function	Country	Location	Grid Connection
32	[19]	2021	Single Heuristic Algorithm	AEO	PV/WT/ES	Economic + Reliability + Technical	COE + LPSP + DEE	Egypt		On/Off-grid
33	[20]	2020	Combined Heuristic Algorithm	BBO + PSO	PV/WT/ES	Reliability	RI	India		On/Off-grid
34	[54]	2018	Traditional Methods	DP	PV/ES	Economic	RE	Spain		Grid-connected
35	[55]	2016	Single Heuristic Algorithm	BAT	PV/WT/ES/DG	Reliability + Technical	PL + VD	India		Grid-connected
36	[56]	2021	Combined Heuristic Algorithm	CSO + PSO	PV/WT/ES	Economic + Reliability + Technical	COE + LOLE + VD	Iran		Grid-connected
37	[57]	2018	Combined Heuristic Algorithm	PSO + GWO	PV/WT/ES/DG	Economic + Environmental	TAC + CE	Egypt	Buildings	Grid-connected
38	[58]	2017	Single Heuristic Algorithm	CS	PV/WT/ES	Economic + Technical	TAC + GEI	Algeria	Other	Grid-connected
39	[59]	2014	Traditional Methods	iterative	PV/WT/ES/DG	Reliability + Economic	UL + NPC		Buildings	stand-alone
40	[60]	2018	Combined Heuristic Algorithm	GA + PSO	PV/WT/ES	Economic + Reliability	NPC + LPSP	Iran	Micro-Grid	stand-alone
41	[61]	2014	Single Heuristic Algorithm	GA	PV/WT/ES/DG	Economic + Environmental	LCOE + NPC + CE	China	Micro-Grid	stand-alone
42	[62]	2015	Single Heuristic Algorithm	PSO	PV/WT/ES	Economic	LCC	Iran	Buildings	stand-alone
43	[63]	2016	Single Heuristic Algorithm	ACO	PV/WT/ES/DG	Economic	TAC	India	Microgrid	stand-alone
44	[64]	2013	Single Heuristic Algorithm	GA	PV/WT/ES/DG	Economic	NPC	Syria	Microgrid	stand-alone
45	[65]	2020	Single Heuristic Algorithm	SSO	PV/WT/ES/DG	Economic + Reliability	COE + LPSP	Kingdom of Saudi Arabia	Microgrid	stand-alone
46	[66]	2018	Single Heuristic Algorithm	SA-CHS	PV/WT/ES	Economic	LCC	Iran	Microgrid	stand-alone
47	[67]	2016	Single Heuristic Algorithm	NSGA-II	PV/WT/ES/DG	Economic + Technical + Environmental	LCC + DEE + CE	Nigeria	Buildings	stand-alone
48	[68]	2012	Single Heuristic Algorithm	NSGA-II	PV/WT/ES	Reliability + Environmental	LPSP + EE		Buildings	stand-alone
49	[69]	2014	Single Heuristic Algorithm	ABC	PV/ES	Technical + Economic	RF + LCC	Egypt	Microgrid	stand-alone
50	[70]	2018	Software Based	HOMER	PV/ES/DG	Economic + Environmental	COE + NPC + CE	Bangladesh	Microgrid	stand-alone
51	[71]	2020	Traditional Methods	MILP	PV/WT/ES	Economic	TAC		Other	stand-alone
52	[72]	2018	Combined Heuristic Algorithm	HS + SA	PV/WT/ES/DG	Economic	LCC	Iran		stand-alone
53	[73]	2020	Single Heuristic Algorithm	PSO	PV/WT/ES/DG	Economic + Technical	NPC + RF + LCOE	Algeria	Buildings	stand-alone
54	[74]	2022	Software Based	HOMER	PV/WT/ES/DG	Economic	NPC	India	Microgrid	stand-alone
55	[75]	2012	Single Heuristic Algorithm	DE	PV/WT/ES/DG	Economic + Reliability + Environmental	NPC + UL + CE	Buildings	stand-alone	
56	[76]	2022	Software Based	HOMER	PV/WT/ES	Economic	COE + LHC	Oman		Grid-connected
57	[77]	2020	Single Heuristic Algorithm	NPO	PV/WT/ES/DG	Economic + Technical + Environmental	LCC + DEE + CE	Iraq	Buildings	stand-alone
58	[78]	2020	Software Based	HOMER + QRod™+ PROSPER™	PV/WT/ES	Economic	NPC + LCOE		stand-alone	
59	[79]	2019	Single Heuristic Algorithm	FPO	PV/ES	Economic	TAC	Egypt		stand-alone
60	[80]	2020	Software Based	HOMER	PV/WT/ES/DG	Economic + Technical + Environmental	NPC + RF + COE + CE	Other	stand-alone	
61	[81]	2017	Single Heuristic Algorithm	MPSO	PV/WT/ES/DG	Economic + Reliability	LCOE + LPSP	Sweden	Microgrid	stand-alone
62	[82]	2016	Traditional Methods	LP	PV/WT/ES	Economic	NPC			stand-alone
63	[83]	2020	Hybrid Models	SEVERAL MODELS	PV/WT/ES	Economic	NPC			stand-alone

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Table 1 (*continued*)

Row	Reference	Year	Type of Solving Techniques	Solving Techniques	Combination Type	Type of Objective function	Objective function	Country	Location	Grid Connection
64	[84]	2011	Traditional Methods	DA	PV/WT/ES/DG	Economic	NPC	–	Microgrid	stand-alone
65	[85]	2017	Combined Heuristic Algorithm	GA + PSO	PV/WT/ES	Economic	NPC		Buildings	Grid-connected
66	[86]	2018	Combined Heuristic Algorithm	HS + SA	PV/WT/ES	Economic	LCC	Iran	Buildings	stand-alone
67	[87]	2014	Traditional Methods	DA	PV/WT/ES	Economic	TCC + LCOE	Tunisia	Buildings	stand-alone
68	[88]	2019	Single Heuristic Algorithm	MCSO	PV/ES/DG	Reliability + Economic	LPSP + NPC	Iran		stand-alone
69	[89]	2017	Single Heuristic Algorithm	GA	PV/ES	Economic	COE	Switzerland	Buildings	Grid-connected
70	[17]	2010	Traditional Methods	SO	PV/WT/ES	Economic	LCC		Microgrid	stand-alone
71	[21]	2019	Software Based	HOMER	PV/WT/ES	Economic + Technical	NPC + COE + RF	Bangladesh	Microgrid	On/Off-grid
72	[90]	2022	Single Heuristic Algorithm	NSGA-II	PV/WT/ES/DG	Economic + Environmental	NPC + COE + CE	Bangladesh	Microgrid	stand-alone
73	[91]	2017	Software Based	HOMER	PV/WT/ES	Economic	COE + NPC	India	Microgrid	
74	[92]	2018	Traditional Methods	LP	PV/WT/ES	Economic	LCOE		Buildings	stand-alone
75	[93]	2016	Software Based	HOMER	PV/WT/ES	Technical + Reliability	NB + LPSP	Oujda	Buildings	stand-alone
76	[94]	2018	Single Heuristic Algorithm	MDE	PV/WT/ES/DG	Economic + Reliability	COE + LPSP	Saudi Arabia	Buildings	
77	[95]	2020	Single Heuristic Algorithm	MGWO	PV/WT/ES	Economic + Reliability + Technical	LCOE + LPSP + DEE	Rural Areas	Other	stand-alone
78	[96]	2016	Software Based	HOMER	PV/WT/ES	Economic + Environmental	COE + CE	India	Buildings	stand-alone
79	[97]	2021	Software Based	HOGA	PV/WT/ES/DG	Economic	COE + NPC	France	Buildings	stand-alone
80	[98]	2021	Single Heuristic Algorithm	MPSO	PV/WT/ES/DG	Economic	COE + NPC	Kenya	Microgrid	stand-alone
81	[99]	2019	Single Heuristic Algorithm	FPO	PV/WT/ES	Economic + Reliability	NPC + LOEE + LOLE	Iran	Microgrid	stand-alone
82	[100]	2021	Single Heuristic Algorithm	AEFA	PV/WT/ES/DG	Economic	TAC	Morocco		
83	[101]	2020	Single Heuristic Algorithm	WOA	PV/WT/ES	Economic	COE	Egypt		Grid-connected
84	[102]	2022	Single Heuristic Algorithm	COA	PV/ES/DG	Economic + Environmental	TAC + CE	Hotan County	Microgrid	
85	[103]	2022	Software Based	HOMER	PV/WT/ES/DG	Economic	NPC	Bangladesh	Microgrid	stand-alone
86	[104]	2020	Single Heuristic Algorithm	SOA	PV/WT/ES	Economic	LCOE	China		Grid-connected
87	[105]	2019	Traditional Methods	Numerical	PV/ES	Economic	RE	Finland		stand-alone
88	[106]	2023	Traditional Methods	MILP	PV/ES	Economic + Reliability	COE + LPSP	Saudi Arabia		
89	[107]	2018	Single Heuristic Algorithm	NSGA-II	PV/ES/DG	Economic	LCOE	Indonesia		stand-alone
90	[108]	2020	Traditional Methods	MILP	PV/ES	Economic + Reliability	LCC + LPSP + PC	JKUAT	Other	Grid-connected
91	[109]	2020	Combined Heuristic Algorithm	ABC + PSO	PV/ES	Economic	COE	India	Buildings	Grid-connected
92	[110]	2020	Single Heuristic Algorithm	MDE	PV/WT/ES	Reliability + Economic	LPSP + LCOE	China		stand-alone
93	[111]	2018	Single Heuristic Algorithm	NSGA-II	PV/WT/ES	Economic + Reliability	COE + RI	Tunisia		stand-alone
94	[112]	2019	Single Heuristic Algorithm	CS	PV/WT/ES/DG	Economic	COE			stand-alone
95	[113]	2021	Single Heuristic Algorithm	ALO	PV/WT/ES	Reliability + Economic	LPSP + LCOE		Grid-connected	
96	[114]	2022	Single Heuristic Algorithm	MSSA	PV/WT/ES/DG	Economic + Reliability	COE + LPSP	Algeria		stand-alone
97	[115]	2019	Traditional Methods	Numerical	PV/ES	Economic	TAC	Yemen		stand-alone
98	[116]	2020	Single Heuristic Algorithm	MOP	PV/ES	Reliability + Economic + Technical	LPSP + COE + RF	Egypt	Microgrid	Grid-connected

(*continued on next page*)

Table 1 (*continued*)

Row	Reference	Year	Type of Solving Techniques	Solving Techniques	Combination Type	Type of Objective function	Objective function	Country	Location	Grid Connection
99	[117]	2016	Single Heuristic Algorithm	MBA	PV/WT/ES/DG	Economic	TAC	Egypt	Microgrid	
100	[118]	2019	Single Heuristic Algorithm	WOA	PV/WT/ES	Economic	LCOE			stand-alone
101	[119]	2019	Single Heuristic Algorithm	NSGA-II	PV/ES	Economic + Reliability	TAC + LPSP		stand-alone	
102	[120]	2017	Traditional Methods	ANN	PV/ES	Technical	GEI		Buildings	Grid-connected
103	[121]	2014	Single Heuristic Algorithm	MOP	PV/WT/DG	Economic + Reliability	COE + RI			stand-alone
104	[122]	2021	Combined Heuristic Algorithm	FA + HS	PV/WT/ES	Economic	NPC			
105	[123]	2016	Single Heuristic Algorithm	FFO	PV/WT/ES/DG	Economic + Environmental	TAC + CE		Microgrid	stand-alone
106	[124]	2018	Single Heuristic Algorithm	NSGA-II	PV/WT/ES	Economic + Reliability	TAC + LPSP	Tunisia		stand-alone
107	[125]	2022	Software Based	HOMER	PV/WT/ES/DG	Economic + Technical	NPC + COE + RF	Microgrid	stand-alone	
108	[126]	2018	Single Heuristic Algorithm	NSGA-II	PV/WT/ES	Economic	COE			
109	[127]	2018	Traditional Methods	DP	PV/WT/ES/DG	Technical + Environmental	RF + FC + CE		stand-alone	
110	[128]	2016	Single Heuristic Algorithm	PSO	PV/WT/ES	Economic	TAC			Grid-connected
111	[129]	2017	Traditional Methods	MINLP	PV/ES	Economic	COE			stand-alone
112	[22]	2022	Software Based	HOMER	PV/WT/ES/DG	Economic	NPC	Thailand	Microgrid	On/Off-grid
113	[130]	2021	Software Based	HOMER	PV/ES	Economic + Environmental	LCOE + CE	Campus & Institution	Grid-connected Buildings	
114	[131]	2020	Single Heuristic Algorithm	MPSO	PV/ES	Economic	PP + LCC			

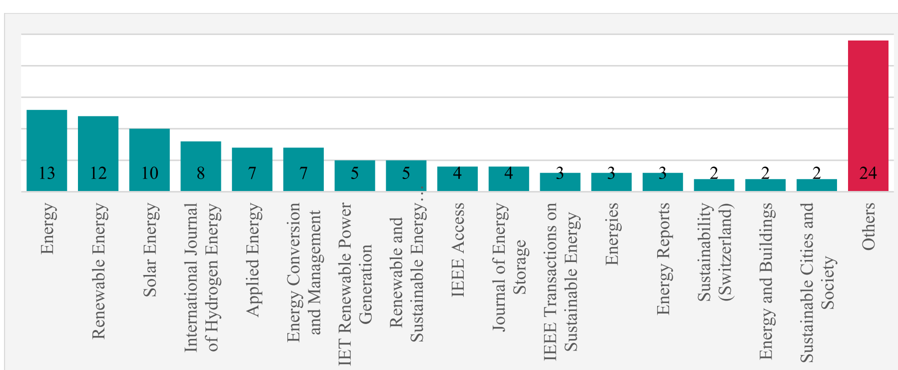


Fig. 6. Publisher of the selected papers.

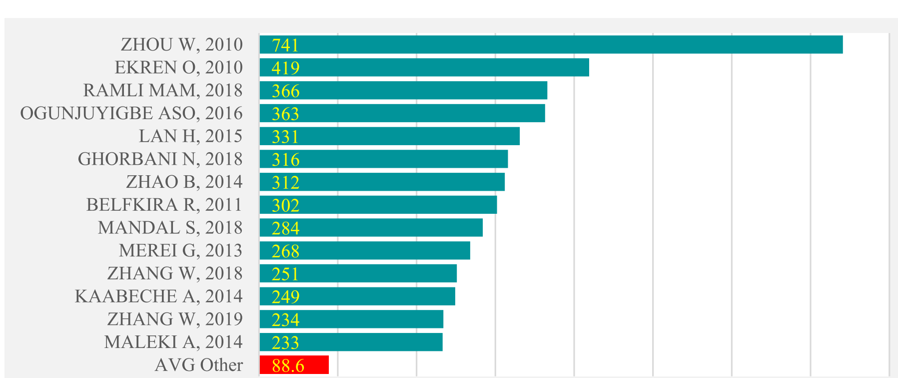


Fig. 7. Citation rate of articles.

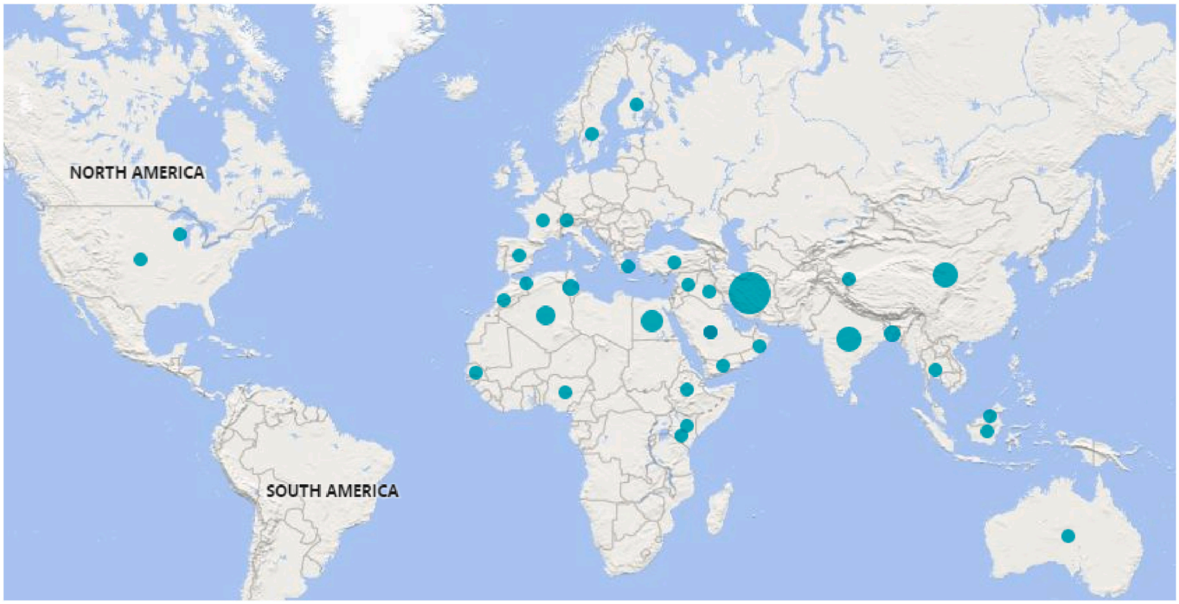


Fig. 8. Countries-based distribution of research.

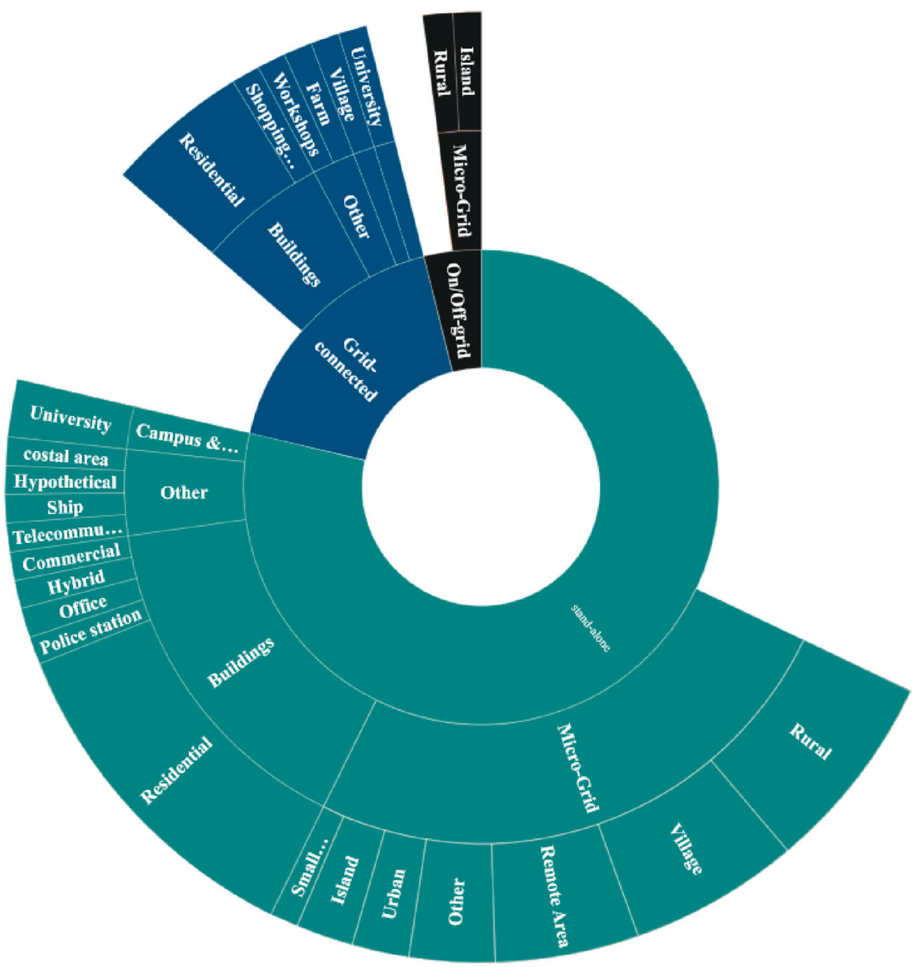


Fig. 9. Proportion of articles in different grid connections for the combination of sources.

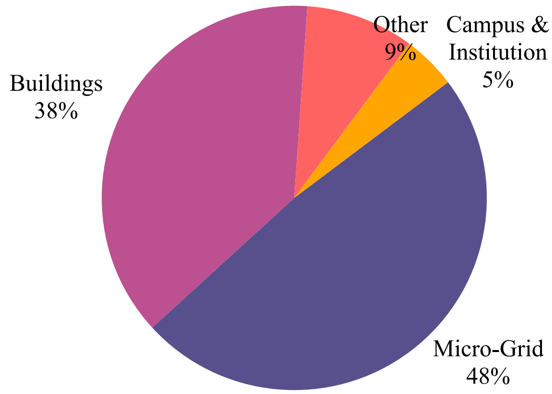


Fig. 10. Proportion of application of a combination of sources.

decision variables, objective functions, parameters and assumptions, and solving techniques) for determining the optimal combination of PV-based renewable energy sources in both grid-connected and off-grid scenarios across different locations.

3. Decision variables

The decision variables differ based on the facilities considered in the combination models. Fig. 16 presents the proportion of facility combinations in all the 114 articles. According to Fig. 16, PV/WT/ES and PV/WT/ES/DG are the most common combinations in the evaluated models. Additionally, ES is used alongside the generation sources in all the reviewed papers except [121] which only considers the PV/WT/DG.

Considering the decision variable as x_i where $i \in (PV, WT, ES, DG)$, x_i can be an integer, continuous, or binary variable. In the integer case, the capacities of each PV panel, WT, ES, and DG are predefined and the model aims to find the optimal value of x_i as the number of PV panels, wind turbines, diesel generators, and battery storage [132–134]. To reduce model complexity, the integer characteristic of x_i, representing the number of generation and storage sources, can be neglected. Similarly, instead of defining the number of generation and storage sources as decision variables, their capacities can be defined as continuous decision variables in the model [135]. In some other research in the literature, where different PV panels or battery types are considered, binary variables are defined to select a specific type in the result.

3.1. PV/ES

PV-ES is one of the common combinations of PV systems for households suitable for both on-grid and off-grid setups [32]. The energy flow configurations for these combinations are shown in Fig. 17. In the grid-connected scenario, the demand can be met by PV, storage, or grid. In the off-grid scenario, also referred to as stand-alone, P_{im} and P_{ex} are equal to zero, and energy shortages occur when demand exceeds the sum of PV generation and stored energy in ES [129].

Fig. 18 depicts the energy at time t in both grid-connected and stand-alone scenarios. In a basic grid-connected system, four scenarios may occur as described below. However in an advanced system, where

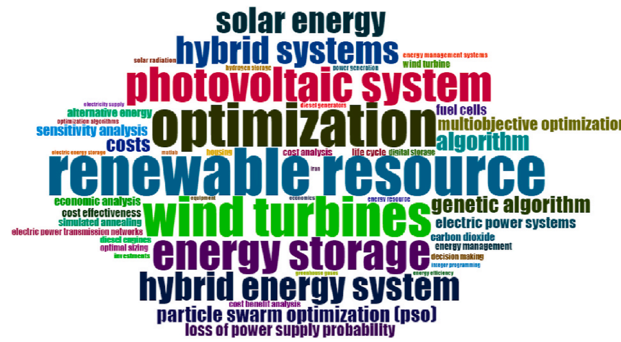


Fig. 12. Word cloud.

storage degradation costs are managed, the energy flow should be determined by another model [120].

- When the generated energy exceeds both the demand and the storage capacity any surplus will be exported to the grid. In scenarios with export limitations, exports are capped at specific daily or hourly values, requiring the use of another model to determine optimal export times.
- If the generated energy is greater than the demand but less than the combined demand and available storage capacity, the battery will store the surplus energy.
- When the generated energy is less than the demand but the stored energy is sufficient to cover the shortfall, the battery will provide the necessary energy.
- In cases where the shortfall between generated energy and demand exceeds the stored energy, the battery will be fully discharged, and the remaining demand will be met by grid supply.

In the stand-alone case, four different scenarios may occur.

- If the generated energy exceeds both the demand and the remaining battery capacity, the battery will become fully charged, and the excess energy will be discarded.
- When the generated energy is more than the demand but less than the total demand and the remaining battery capacity, the battery will charge without any energy being wasted.
- If the generated energy is less than the demand, yet the shortfall can be covered by the stored energy, the battery will discharge to provide the necessary power.
- When the combined total of generated and stored energy falls short of the demand, the system will experience an energy shortfall.

Fig. 19-a and 19-b present the proportions of applications and types of objectives in both grid-connected and off-grid scenarios of PV/EV combination in different papers. Based on the result, the PV/EV combination is usually used in buildings [89,109,120] and in cases with small to mid-level demand with applications proposed equally in both grid-connected and off-grid scenarios. In most cases economic considerations are one of the objective functions and reliability issues are commonly addressed in off-grid scenarios [69].

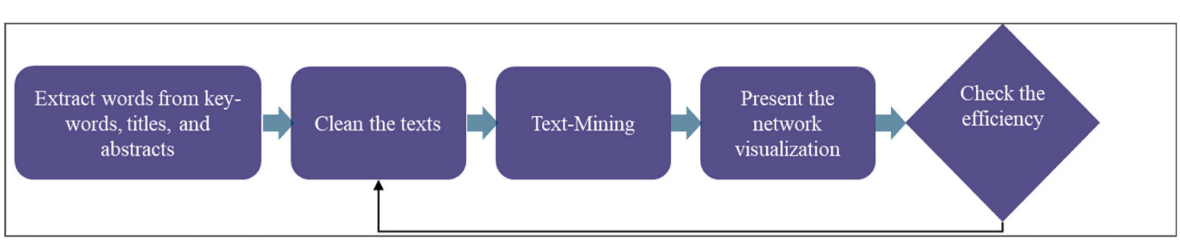


Fig. 11. Text mining process.

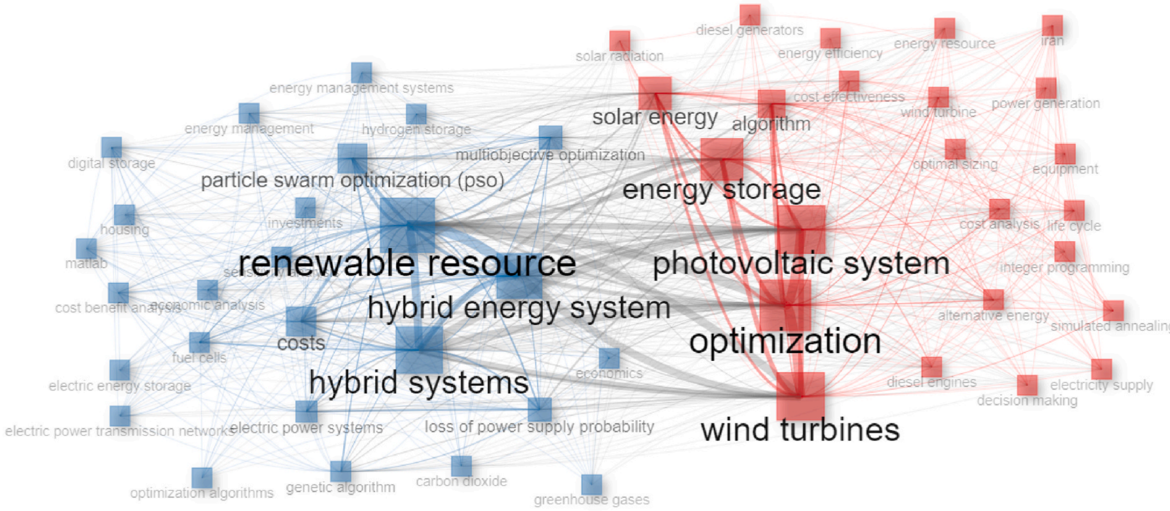


Fig. 13. Word map.

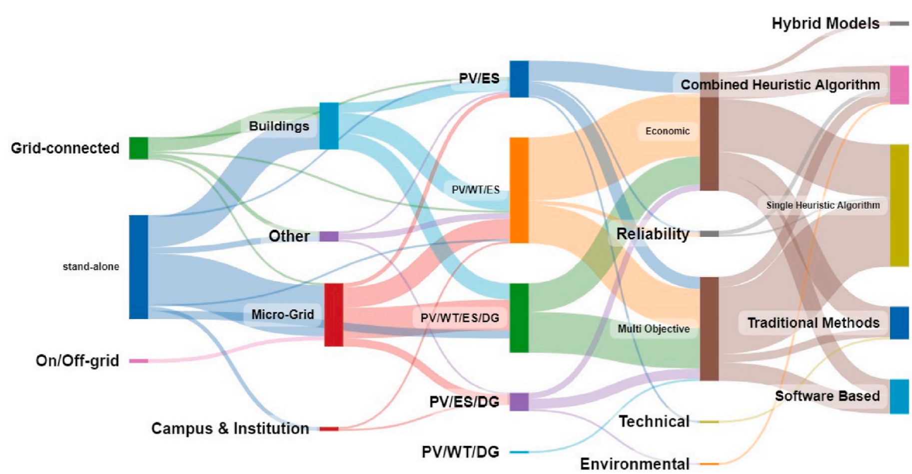


Fig. 14. comparing the criteria.

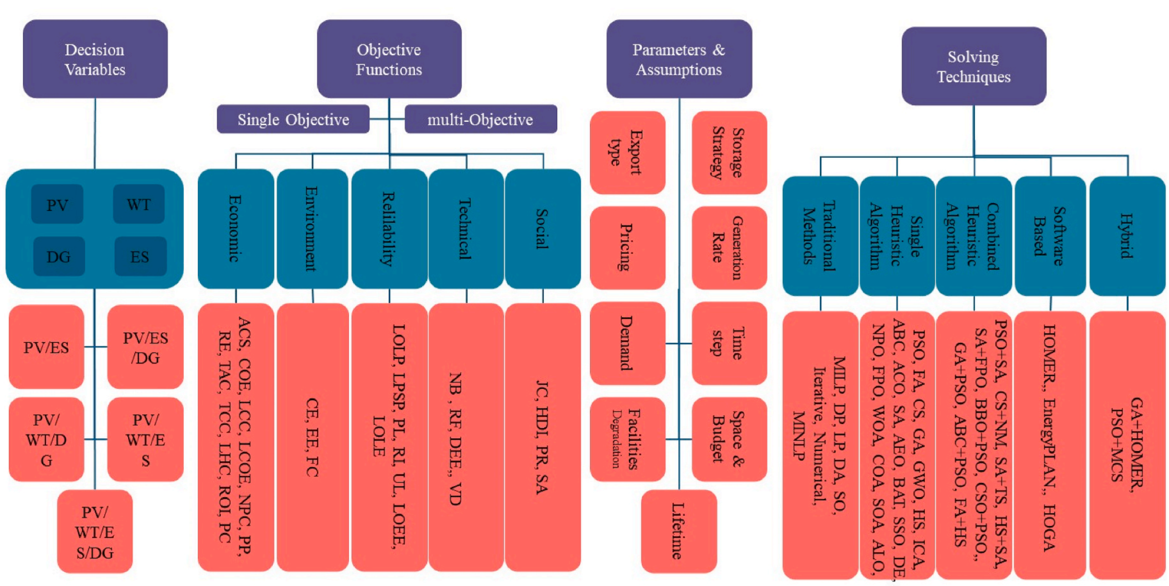
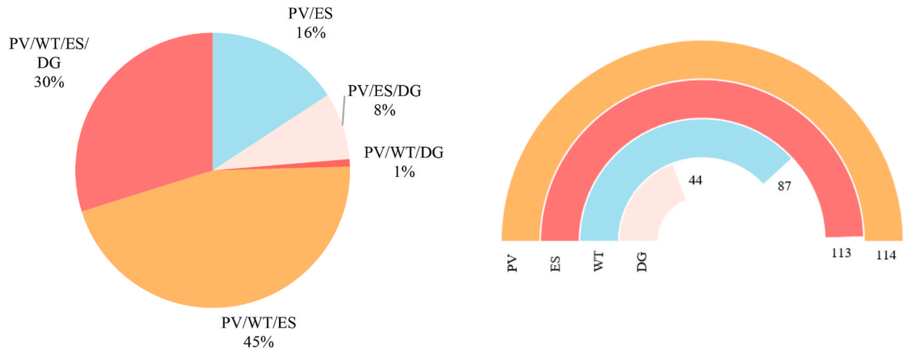


Fig. 15. review farmwork.



a) Different combinations b) The use of facilities out of 114 articles

Fig. 16. Proportion of combination of sources.

3.2. PV/ES/DG

Due to uncertainty in energy output from PV systems and the risk of loss of load in off-grid cases, DG can be used as reserve sources to enhance the system as shown in Fig. 20 [102]. Fig. 21 presents the application of this combination in the reviewed papers as well as the used objective functions. Based on Fig. 21 PV/ES/DG combination is only used for off-grid scenario with environmental-related and economic objective functions being considered in most cases [33,102]. Additionally, the PV/ES/DG combination is more frequently applied in microgrid cases compared to other situations in the literature.

In one study [29], HOMER is used to identify the optimal combination of PV/ES/DG for an office, resulting in configuration of 19.4 KW for PV, 21 kW for DG, and a 220 kWh battery, with the cost of energy (COE) at 0.21 $/kWh and net present cost (NPC) at $110,191. Another study employed HOMER to find the best mix of sources for a stand-alone system in Bangladesh, achieving a combination of 73 kW PV, 57 kW DG, and 387 kWh battery, with the COE at 0.37 $/kWh and NPC at $357,284 [70]. Additionally, other studies [50,88], propose optimal source combinations for stand-alone cases in Iran, featuring capacities of 80 m^2 PV, 8 kW DG, and thirty-three 155Ah batteries, and 115 kW PV, 54 kW DG, and a 14 kW fuel cell, respectively.

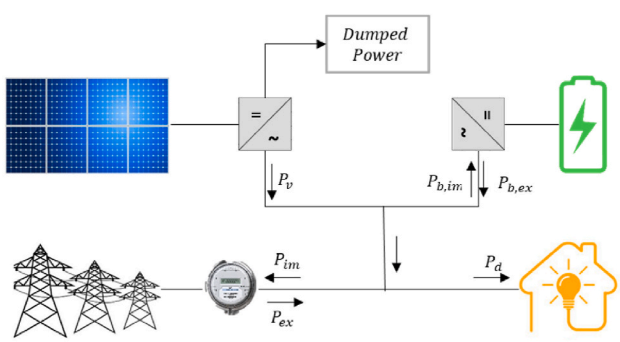


Fig. 17. The energy flow in the PV/ES combination.

3.3. PV/WT/ES

Due to environmental concerns associated with DG, WT is often favored in research over DG, in conjunction with PV and ES systems, to enhance system reliability [121]. The energy flow in PV/WT/ES combinations is presented in Fig. 22, and its application is presented in Fig. 23. Based on the results, such a combination is predominantly used in stand-alone systems [34,36,39,41], with only three articles comparing stand-alone and grid-connected scenarios. Given the weather-dependent and stochastic nature of both PV and WT generation rates, reliability indices are commonly used alongside economic factors as objective functions in these studies [42,43,51,52].

Studies [40,46], and [62] each employed a single heuristic algorithm to determine the optimal mix of PV/WT/ES for a stand-alone residential building in Iran. Their findings were 6.24 kW PV, 2 kW WT, and 65 units of 2.1 kWh batteries at a total annual cost of $4619; 9 kW PV, 1 kW WT, and a 23.1 kWh battery with a total cost of $5652; and 4.93 kW PV, 4 kW

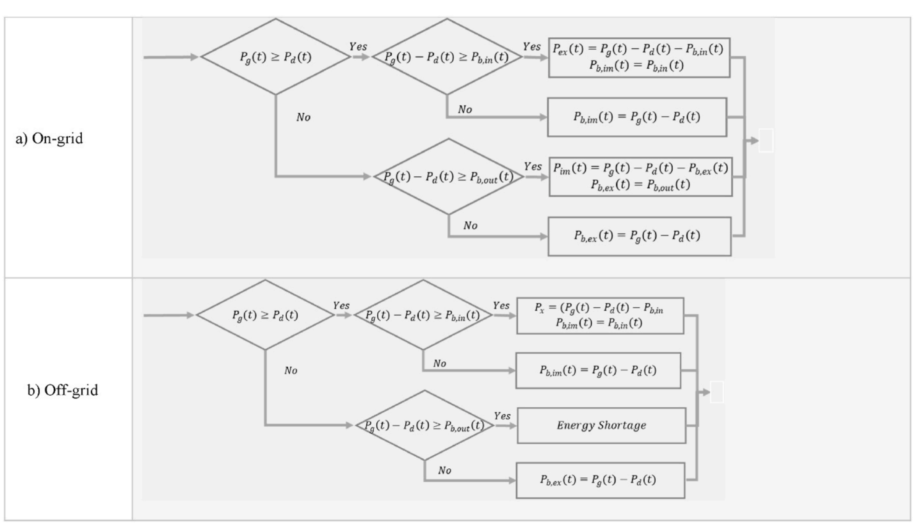


Fig. 18. Energy flow.

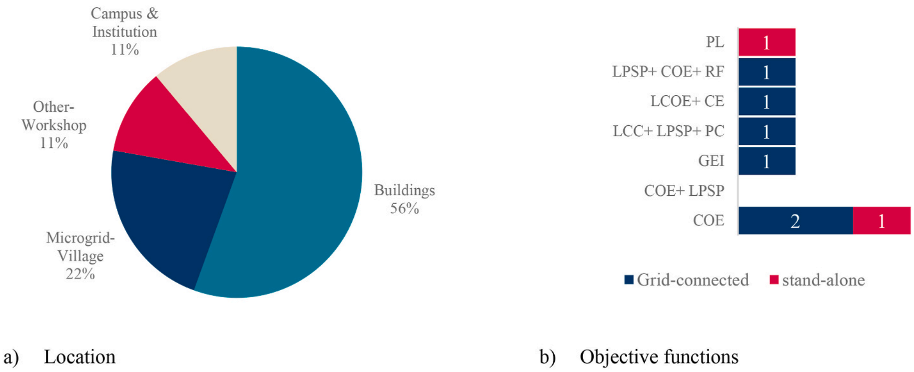


Fig. 19. Proportion of using PV/ES in a) different locations and b) objective functions.

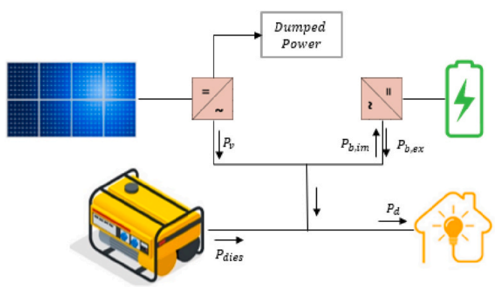


Fig. 20. The energy flow in the PV/ES/DG combination.

WT, along with 63 units of 150 Ah batteries at a lifecycle cost of $68, 588, respectively. In a separate study [93], found that for Oujda, the optimal system consists of 3.12 kW PV, 5 kW WT, and a 40 kWh battery, with a COE of $0.375/kWh and an NPC of $37,818. For a stand-alone microgrid in China [25], applied multi-objective PSO, resulting in a combination of 13,786 kW PV, 3,750 kW WT, and 5,376 kW PHS, with a COE of 0.2345. Another study in Egypt [101] determined an optimal setup of 314 kW PV, 30 kW WT, and 2,504m^3 PHS, with a COE of $0.2173.

3.4. PV/WT/ES/DG

Increasing the demand values as well as uncertainty on the demand patterns and generation rate of PV and WT, achieving a reliable system solely with PV/WT/ES becomes expensive [37,97]. Therefore, DG is used to reduce the cost while maintaining the same level of reliability [47,61]. Fig. 24 depicts the energy flow in such a combination and Fig. 25 presents its application in the selected papers. In 61 % of cases such as [63–65,74], this combination is used for microgrids, primarily in islands and rural areas, while in 35 % of cases including [67,73,77,97], providing energy to stand-alone residential and commercial complexes

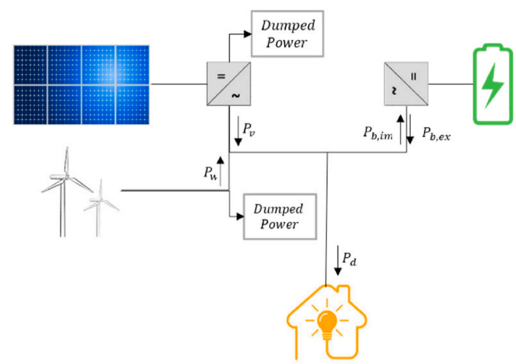


Fig. 22. The energy flow in the PV/WT/ES combination.

is suggested. All the papers used this combination in off-grid scenarios, with some comparing the results to grid-connected situations. Moreover, environmental and technical objectives are considered alongside economic factors to determine the optimal configuration of this system.

4. Objective functions

In terms of objective functions, the models can be categorized into two groups: single-objective models and multi-objective models [81]. In a single-objective model, a specific objective function, such as minimizing generation cost or carbon emission rate, is considered, and a model is used to optimize that problem [123]. Hence, the applied model usually generates a specific solution [64]. In multi-objective models, two or more objective functions that may conflict with each other are considered, producing a set of non-dominated solutions [90,116,136]. The proportion of objective types across various sources of PV-based combination systems is presented in.

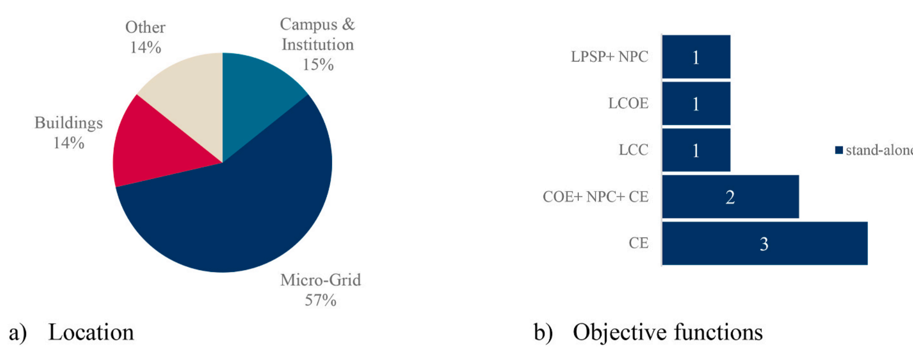


Fig. 21. Proportion of using PV/ES/DG in a) different locations and b) objective functions.

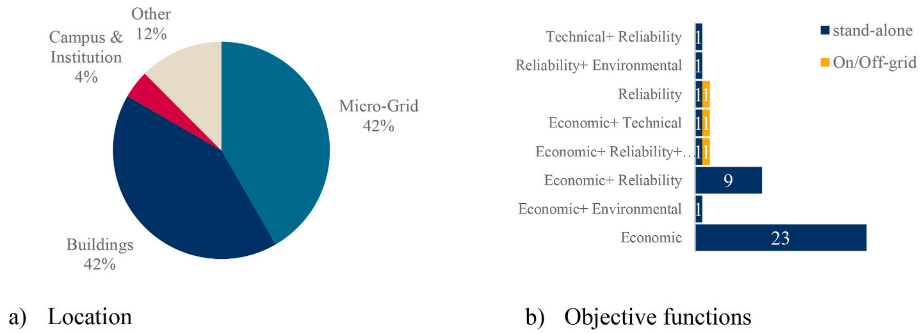


Fig. 23. Proportion of using PV/WT/ES in a) different locations and b) objective functions.

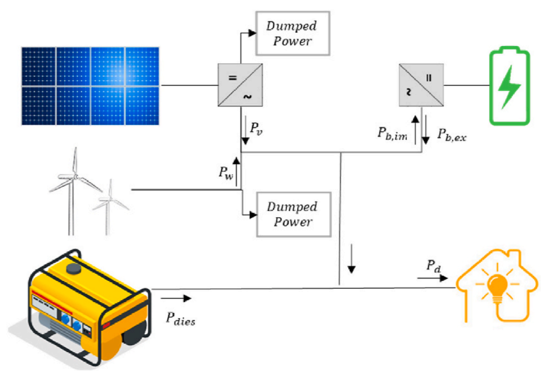


Fig. 24. The energy flow in the PV/Wind/Diesel/Battery combination.

Fig. 26, showing that both single-objective and multi-objective models are used almost equally. Among all the objective functions, economic-related objectives are predominant: 89 % of single-objective models focus on economic purposes, and in all multi-objective models, at least one of the objectives is economic-related.

Based on the literature, five groups of objective functions, namely reliability-based, economic-related, environmental-based, social-based, and technical-based functions, and their combinations (in multi-objective models) are discussed in the literature as presented in Fig. 27.

4.1. Economic-related indicators

The financial objectives regarding the project cash flow including investment cost, maintenance, and operational cost, are among the most commonly used objective functions. In this group of indicators, the financial values of different scenarios are compared and the optimal one is selected [137]. Fig. 28 shows the proportion of different economic-related factors used in the reviewed papers, which indicates that NPC [22,28,59,60,64,75,84,85,98,122] and the cost of electricity (COE) [27,89,94,95,101,111,112,114,126] are the most used economic-related objective function in the literature. Additionally, total annual cost (TAC), which includes the purchasing cost, operation and maintenance cost, and investment cost divided by the project life cycle, is another commonly used objective function [37–39,48,58,71,79,100,115,117,119,128].

TAC is simple, but not an ideal measure, especially for comparing different projects with varying demands. In such cases, COE is a better measure for comparing different plants even with different capacities [138]. For countries with a high inflation rate, the result of Net Present Value (NPV) is also used as an objective function to determine the optimal combination of renewable sources [17,35,44,50,62,66,128,131]. used life cycle cost (LCC) functions to optimize the number of PV panels and the capacity of wind turbines for a gird-connected problem. Levelized cost of energy (LCE) [49,87,110,113,118] and cumulative saving (CS) are other financial functions used for determining the optimum combination [1,104,107,139].

4.2. Reliability-related indicators

The generation rate of PV varies throughout the year as it is related to different external parameters such as incident solar radiation and sun angle. Therefore, considering the reliability of the system to ensure the demand coverage under various conditions is important [45,70]. Different reliability-based objective functions are considered mostly in the off-grid cases to determine the optimum combination of sources. Fig. 29 presents the proportion of reliability-based objective functions in the literature, which shows loss of power supply probability (LPSP) is the most commonly used reliability-based objective function with a frequency of 65 % [53,140].

Loss of load expected (LOLE) [56] and loss of load probability (LOLP) [24] are two other commonly used reliability-based indexes. LOLE represents the expected number of hours per year when demand exceeds

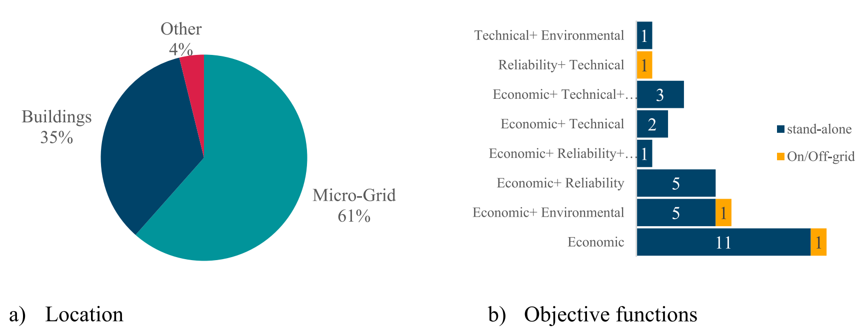


Fig. 25. Proportion of using PV/WT/ES/DG in a) different locations and b) objective functions.

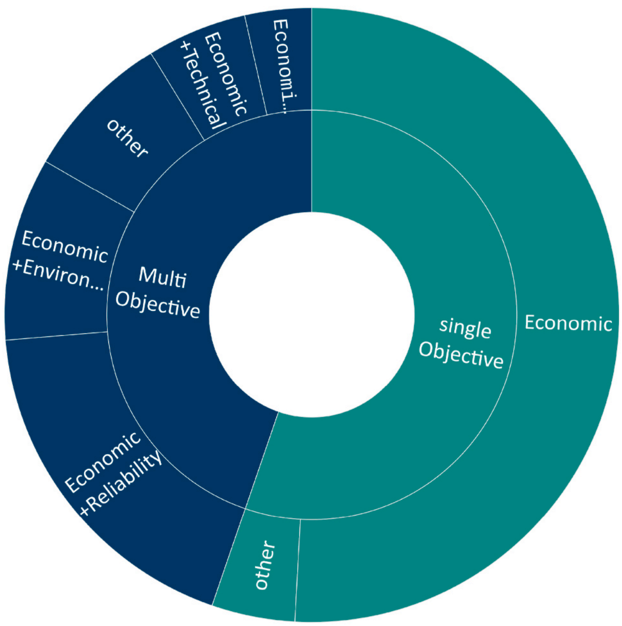


Fig. 26. Proportion of using single/multi-objective models for the combination of sources.

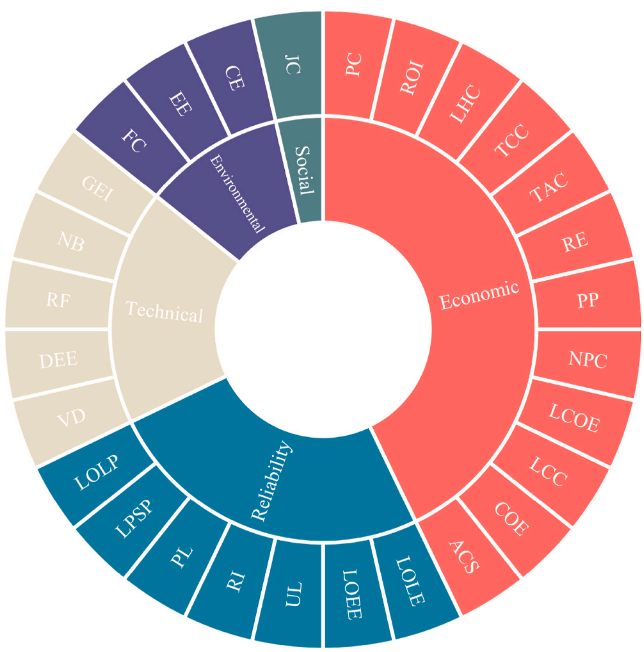


Fig. 27. List of objective functions.

generation and is used to evaluate the required installed capacity based on peak-period, while LOLP is used to evaluate the probability of shortage during this time [24]. Other reliability-based objective functions include deficiency of power supply probability (DPSP) [141], and loss of energy expected (LOEE) [99].

4.3. Environmental-related indicators

Solar energy is clean and environmentally friendly, with its environmental advantages being among its primary benefits. Fig. 30 presents the proportion of environmental-related objective functions in the reviewed papers, which shows minimizing Carbon Emission (CE) is a common objective function to evaluate the positive environmental

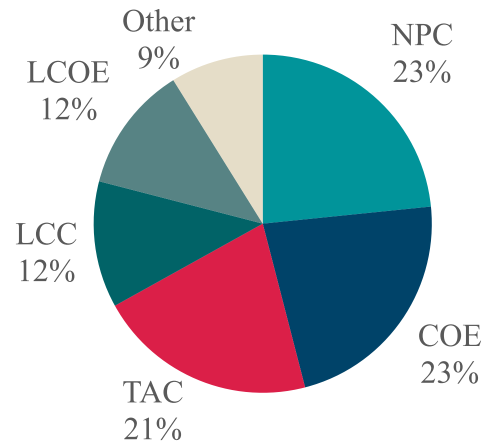


Fig. 28. The proportion of using Economic-related objective functions for the combination of sources.

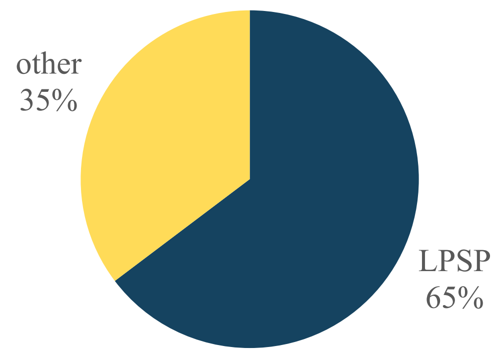


Fig. 29. Proportion of using Reliability objective functions for the combination of sources.

impacts of source combinations [26,29,90,102]. Embodied energy (EE) and fuel consumption [FC] are other commonly used environmental-related objective functions in the literature [68,127].

4.4. Technical indicator

This group of objective functions evaluates the technical aspects of the problem. Fig. 31 presents the proportion of technical factors used in the reviewed papers which shows the renewable fractions (RF) and dumped and excess energy (DEE) are the most commonly used objective functions of this group [19,73,80]. Total energy generated (TEG) evaluates the total produced energy during the project's lifetime [139], total

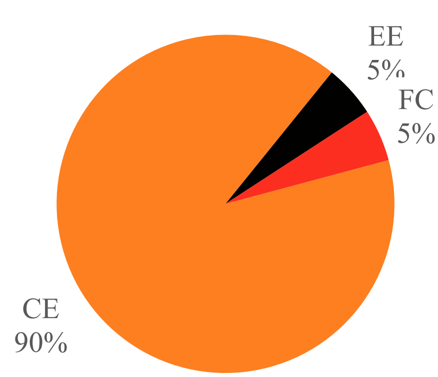


Fig. 30. Proportion of using environmental-related objective functions for the combination of sources.

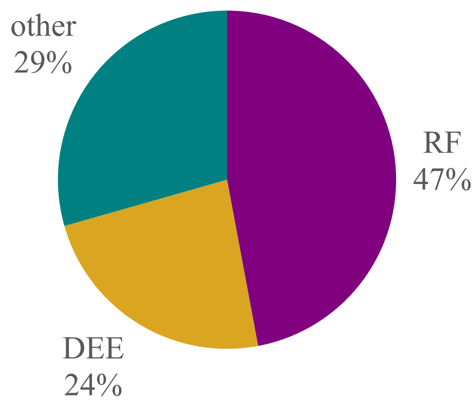


Fig. 31. Proportion of using technical-related objective functions for the combination of sources.

area required (TAR) and power balance (PB) which respectively assess the total space needed for installation and the ratio of total generated energy to total demand, are other common indicators in this group [55, 139]. Demand supply fraction (DSF) is also considered for evaluating of the optimal combination by calculation of the ratio of hours of the year in which generation is higher than demand to all hours of the year [139].

4.5. Social indicators

Besides the mentioned objective functions, social-related objective functions represent another group that is less frequently used in the literature. This group of indicators is usually used to determine the social impact of renewable sources of energy. Memon et al. [12] considered job creation (JC) including job creation in manufacturing, installation, operation, and maintenance processes as objective functions to determine the optimum capacity of PV, Wind, and storage systems.

To determine the optimum combination of PV with other sources, including Biomass, Wind, Hydro, and fuel-based plants for a country or large area, the portfolio risk (PR) is considered as the objective function [142]. Social acceptance (SA) and human development index (HDI) are other objective functions considered in the literature [1].

5. Model parameters and assumptions

All the mathematical models include specific parameters. In this section, the most used parameters and the most common assumptions for the optimization of renewable source combinations are presented.

5.1. Export type

In most countries, in a grid-connected scenario, over-generation could be exported to the grid at a predefined price, without any restriction on the amount and timing. However, there is a limitation in other countries, especially those countries that are reaching high renewable shares in their energy matrix [143]. In most Australian states, the export limitation is 5 kW or 10 kW. In Germany, a country with over one million PV systems linked to LV networks, individuals possessing installed capacities below 30 kW are restricted from exporting (i.e., generating surplus beyond demand) more than 70 % of their total installation [144]. In Hawaii, the over-generated energy can be exported to the grid only during limited times of the day, and the exported energy from 9 a.m. to 4 p.m. is not compensated [145].

While undeniably efficacious, implementing such an export limit carries substantial economic repercussions for PV owners, potentially serving as a disincentive for the adoption of new PV systems. In the scenario with a limitation on export, the optimal capacity in the solution tends to be lower than the optimum capacity in the scenario without any export limitation [146]. The export limitation should be considered alongside the energy pricing models. If the energy price is fixed during the day, there is no difference between the exporting times, but in the case of dynamic pricing, the exporting time, especially under the export limitation scenario, plays a key role in the models' results [147].

5.2. Storage strategy

By combining renewable sources and storage devices, several possibilities for prioritizing charging or discharging the battery and determining the source of energy for responding to the demand can be defined [148]. The demand can be provided from the generated energy by renewable sources, batteries, or the grid. Additionally, energy generated over demand could be stored or exported to the grid. Determining the optimum source to respond to energy demand as well as the optimum use of over-generated energy could impact the financial parameters of the project.

In the off-grid models, the stored energy should be used any time the demand is higher than the generation rate, while in on-grid cases, three main strategies could be adopted [149]. In the first strategy, with higher priority given to the battery, the stored energy will be used any time the demand is higher than generation, so the battery will charge and discharge frequently. In the second strategy, with lower priority given to the battery, the stored energy is used only during peak periods when retailer prices are higher than off-peak prices [148]. In another strategy, which combines the two other strategies, the optimum priority is determined based on the time and energy pricing model [150]. Based on the study [151], energy costs could be reduced by up to 57 % by using the hybrid strategy and storing power during off-peak times and using the stored power during peak times just by investing in the battery.

5.3. Energy pricing

Energy price is another important external parameter in the evaluation of the optimum combination of energy sources. While in most cases, a constant price is considered for evaluation, the fluctuations in power prices impacts the feasibility of any energy generation system [152–156]. The energy price can vary during the day based on pricing policies, and there are three common pricing methods as presented in Fig. 32: (1) time-of-use (TOU), where the energy price varies at different times (Off-Peak, Mid-Peak, and On-Peak) during the day; (2) Critical peak pricing (CPP), where the energy price depends on consumption values; and (3) Real-time pricing (RTP), where the price varies from time to time [151,157].

Pricing models directly impact the optimum solution and results, and various policies are considered based on the pricing model. In the fixed price model, the timing of energy exports does not influence the outcome. However, in dynamic pricing models, export timing becomes crucial—particularly in scenarios with export limitations. So, scheduling battery charging and discharging during off-peak and peak times, respectively, can significantly reduce energy costs [151,158].

5.4. Generation rate

The generation rate, which depends on several parameters including facility characteristics and meteorological parameters, is another important factor. The generation rate can be evaluated based on the theoretical formulas [159] and the historical data [1].

While the generation rates fluctuate throughout the day, in some research, such as feasibility studies, and linear and nonlinear optimization, a crisp value, equal to the average, minimum, or maximum of historical values, is considered for the generation rate during specific hours [142].

Alternatively, some research treats the generation rate as a stochastic parameter or uncertainty value [160]. Arun, Banerjee [161] assume the PV generation rate follows a normal probability distribution, and then

Fig. 32. Policies of energy price.

Monte Carlo simulation is used to optimize the size of PV and battery. A combination of system dynamics and Monte Carlo simulations has been used by Jeon and Shin [162] to address uncertainty in long-term renewable energy system assessment. Moret, Codina Gironès [163,164] used global sensitivity analysis to evaluate the impact of uncertainty parameters on the decision-making results.

5.5. Energy demand

Energy demand can be considered a deterministic or stochastic parameter as it is influenced by several factors [165]. There are several software applications available such as Equest, EnergyPlus, Dest, and Doe-2 that can be used to assess energy demand using physical models [166]. These applications account for various building and environmental characteristics, including but not limited to, the building's location and climate, solar radiation and shading, materials used in construction, and non-geometric features such as heating and air conditioning systems for prediction [167].

Mavrots et al., and Rezvan et al., treated demand as a stochastic parameter in their models and addressed it using simulation models [168,169]. In another study, demand was considered a fuzzy number and solved by fuzzy programming [168,170]. [171,172] considered the demand with uncertainty ranges and solved using RO.

The general energy demand includes two parts: dispatchable and non-dispatchable, both of which come with uncertain characteristics [173]. It is possible to program dispatchable appliances to run under circumstances without sacrificing user convenience. Examples include water heaters, dishwashers, washing machines, dryers, and air conditioners [174]. Moreover, dispatchable appliances are divided into two categories: equipment that can be adjusted for power and time. Power-adjustable equipment can be flexibly adjusted within their rated power range. Time-adjustable equipment, alternatively, operates at a fixed rated power, but its operating time can be adapted based on demand. This group is further divided into non-interruptible appliances (such as vacuum cleaners and electric water heaters) and interruptible appliances (such as washing machines, dryers, and dishwashers). Important appliances such as security systems, lighting controls, and refrigerators are considered non-dispatchable equipment. Attempting to schedule these loads can pose challenges and potentially lead to significant disruptions to user demand [174].

5.6. Time step

Energy demand and generation rate can be evaluated on different time steps from every second to monthly or even yearly. The model complexity and accuracy of the results will increase by using smaller time steps. The hourly time step is the most used [175].

5.7. Facilities degradation

Degradation is an inseparable characteristic of the facilities. In the PV, every level of the system—cell, module, array, and so on—shows signs of performance decline, with various causes and degradation processes being visible at each level [176]. The primary external elements that are linked to a decline in performance during field operations include temperature, humidity, precipitation, dust, snow, and solar radiation. Degradation is caused by all of these factors at the array level in addition to shading and module incompatibilities [177]. More precisely, at the level of PV cells, corrosion, light-induced deterioration, contact stability, and fractured cells are the main causes of performance loss and potential failure. Degradation happens at the module level because of hot spots, diode failures, glass breakage, delamination, busbar failure, broken interconnects, front surface discoloration, and moisture infiltration in addition to the reliability issues with the individual cells [178].

The degradation of the battery is more challenging because it is dependent on the operation strategy. Based on the Olmos, Gandiaga [179], the battery degradation rate depends on different parameters including Operating Temperature (The ambient temperature is referred to as the operating temperature), Depth-of-Discharge (The difference in State-of-Charge throughout the course of a single cycle), average or Middle-State-of-Charge (deterioration resulting from a 10 % DOD between 90 % and 100 % SOC is typically thought to be different from deterioration happening between 0 % and 10 % SOC), C-rate Charging and Discharging (the normalized battery current compared to its original capacity at Beginning-of-Life under nominal circumstances), and full equivalent cycles (a 100 % DOD is represented by an FEC, which is a complete cycle of charging and discharging).

While the battery degradation rate has uncertain characteristics, it is considered an exact parameter. The yearly loss of capacity due to battery aging is estimated 1 % by Gardiner, Schmidt [180] and 0.4 % by Linssen, Stenzel [181].

In Mohamed, Best [182], instead of a linear degradation function, an exponential function, extracted from the semi-experimental model by Xu, Oudalov [183], with the exact rate considered for the battery degradation rate, was used to account for both cycle and calendric aging mechanisms. Hesse, Martins [184] also used non-linear equations for modeling the battery degradation.

James, Alexander [185], proposed the Weibull distribution with three parameters to estimate the battery life cycle and Aurbach, Zinigrad [186] showed that the two-parameter Weibull distribution provides a higher accuracy rate. Wang, Zhou [187] also showed that battery failure with a threshold of 70 % degradation can be predicted with higher accuracy using the Weibull distribution.

Some research used linearization of the state of health curve to simplify battery degradation [187–189]. Xu, Zhao [190] and Aaslid, Korpås [191] suggest a piecewise linear relaxation of the nonlinear DOD degradation.

5.8. Installation space and budget

Installation space and investment budgets are other parameters that are usually considered unchanged during the planning time scale. Installation space is a crucial and an effective constraint, as solar capacity for households is limited by rooftop space. In this case, the optimal capacities of PV and storage are determined based on the available rooftop space for PV installation [143,192,193].

5.9. Lifetime

The facility's lifetime in the energy management system depends on several external parameters, leading to different assumptions about project lifetime in previous research. Usually, PV module manufacturers provide a 25-year warranty against this loss at 80 % of nameplate capacity; 25 years is commonly used as the lifetime in the literature [194–196]. While Lozano, Ramos [197], Alshammari, Samy [198], and Samy, Sarhan [199] considered the PV life cycle to be 15 years, Khezri, Mahmoudi [143] and Kiptoo, Adewuyi [136], assumed the PV life cycle to be 20 years, Kakoulaki, Szabo [200], Saez, Boer [201] and Han, Garrison [202] considered the 30 years for this parameter.

6. Solving techniques

To solve the optimum combination problem of PV with other sources, numerous techniques are proposed in the literature, which can be categorized into five groups: Traditional Methods [31,105,106,108], Single heuristic Algorithms [62,67,124], Combined Heuristic Algorithms [33,44,51,86], Software-based techniques [70,91,96,103], and hybrid models [39,83]. The techniques used in each group are presented in Fig. 33, and Fig. 34 represents the distribution of these techniques. Due to the complexity of such problems, particularly because of uncertainty characteristics of parameters like demand, generation rate, and degradation rate, single heuristic techniques are the most used in the literature. Based on the results, GA and PSO are the most frequently used techniques, at 23 % and 17 %, respectively. In the software-based model, HOMER is the most commonly used, and in the combined heuristic models, SA + HS is the most frequently used combination [50,72,86], while the PSO is combined more with other algorithms [33,39,44]. In the traditional models, all techniques are used with approximately the same frequency.

Each model comes with its own advantages and disadvantages which are summarized in Table 2.

6.1. Traditional method

Traditional methods are mainly based on mathematical programming and are usually used in problems that do not contain any stochastic parameters. Mixed Integer Linear Programming (MILP) [31,33,106,108] is the most commonly used traditional method and is used to determine the optimum number of PV panels, wind turbines, diesel generators, or batteries with predefined capacities. Mixed Integer Non-Linear Programming (MINLP) is an evolved variant of MILP that considers the non-linear attributes of parameters such as facility degradation, as well as generation and demand rates [129]. Due to the complexity of integer terms in mathematical models, some linear programming (LP) and Dynamic Programming [54] are used in some research by relaxing the integer characteristic of parameters [82,92]. Khalaj et al. [203] used linear programming to optimize the size and number of photovoltaic panels, wind turbine capacity, and battery capacity by minimizing the total levelized costs. Madhelopa et al. [204] also used linear programming to determine the optimal size of a grid-connected PV–wind hybrid system in South Africa. Nogueria et al. [205] applied linear programming alongside simulation tools to determine the optimal size of PV wind by considering the storage.

6.2. Single heuristic algorithms

Heuristic algorithms include a wide range of algorithms inspired by natural phenomena and are used for NP-Hard problems where computation is costly [46]. Instead of providing the optimum solution, heuristic algorithms search the solution space and propose a solution near the optimum within a reasonable time [100]. These algorithms are commonly used to determine the optimum size of facilities when the demand or generation rates are considered as the stochastic parameters [19]. The most used heuristic algorithms are presented in this section.

6.2.1. Particle swarm optimization (PSO)

PSO is a well-known heuristic algorithm based on the social behavior of bird flocking or fish schooling and was introduced by Kennedy and Eberhart in 1995 [81]. In PSO random combinations of parameters are generated, analogous to locations of birds [24,30,40]. In each iteration, the fitness function of each locations is evaluated. The location is then updated by moving towards the local optimum (personal best) and the best result (global best) is identified (see Fig. 35). The iteration continues until the stopping criterion is met, such as reaching a maximum number of iterations or finding a satisfactory solution [206,207].

6.2.2. Genetic algorithm (GA)

The GA is another widely used heuristic algorithm that was inspired by the process of natural selection and genetics and introduced by John Holland in the 1960s [32]. To define the optimum combination of PV and other renewable sources, as shown in Fig. 36, initially, the number of possible combinations is generated randomly and considered as the initial population. Then, in each iteration, the fitness function of each solution (members of the population called chromosomes) is evaluated based on the objective function, and the new generations are created based on three operators: selection, crossover, and mutation on the members (called parents) of the previous population to reach the best solution [89,208–210].

6.2.3. Simulated annealing (SA)

The SA was inspired by the physical process of annealing in metallurgy and introduced by Kirkpatrick et al., in 1983 [48]. To use SA to determine the optimum combination of renewable sources, as shown in

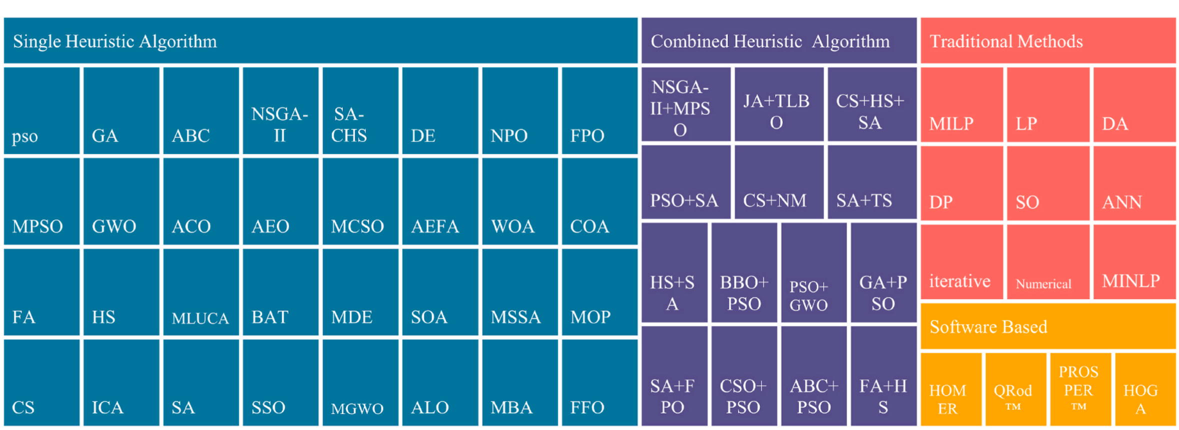


Fig. 33. Solving techniques.

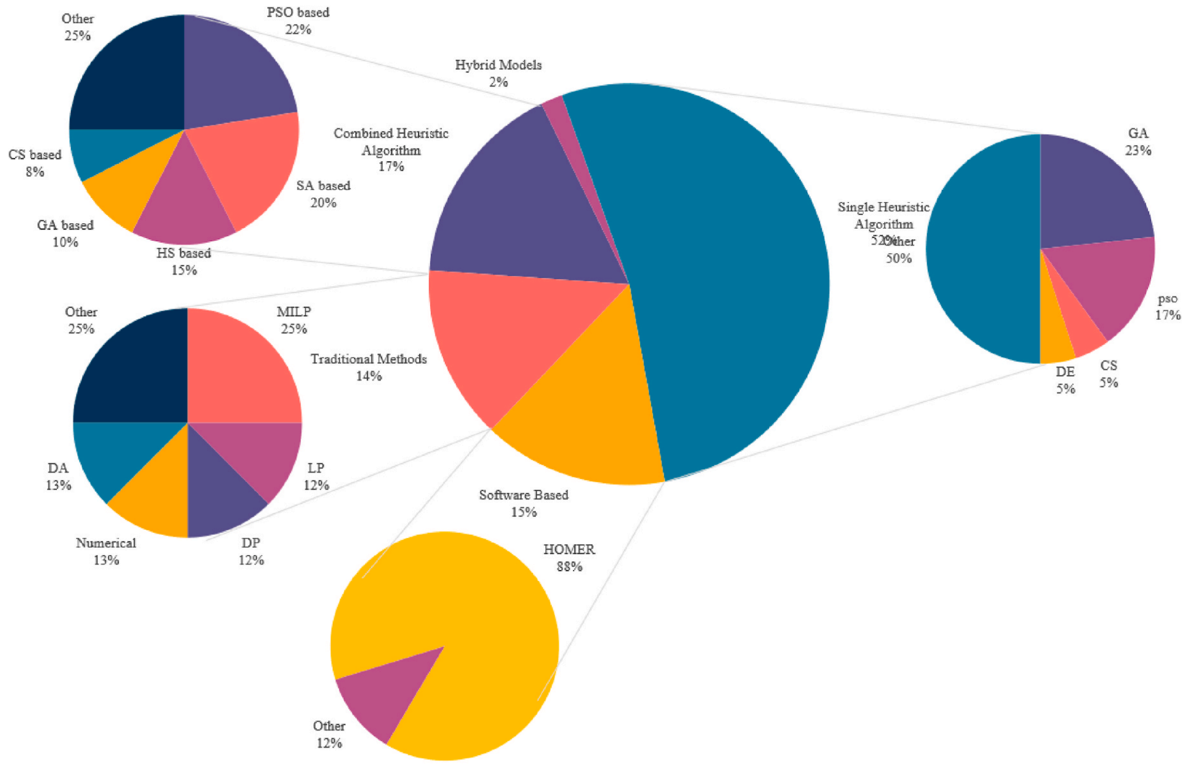


Fig. 34. Proportion of solving models for the combination of sources.

Table 2
Advantages and disadvantages of solving techniques.

Solving Techniques	Advantages	Disadvantages
Traditional Method	Easy to Implement Results in a global optimum solution can be used for multi-objective models	Inappropriate for large-scale problems Low flexibility Time-consuming
Single Heuristic Algorithms	Efficient in calculation Appropriate for complex problems Appropriate for multi-objective case	Large number of iterations in complex problems Possibility of finding a local optimum solution Requires defining and tuning algorithm parameters
Combined Heuristic Algorithms	More accuracy in comparison to a single heuristic algorithm Appropriate for complex problems	Large no of iterations in complex problems Possibility of proposing a local optimum solution Need to define and tune the algorithm parameters
Software Based	Easy to understand Simple methods and convenient to use	Low level of flexibility limitation in time series data type Not suitable for multi-objective models
Hybrid Model	It gives better flexibility in sizing the system	Need to spend time modeming and combining the methods

Fig. 37, initially, a random combination is considered. In each iteration, this combination is compared with a new one. During the initial iterations, the proposed solution is replaced by new ones even if the fitness function does not improve, but as time goes on, the replacement occurs only if the fitness function of the new solution is better than the previous ones [48].

6.2.4. *Artificial bee colony algorithm (ABC)*

The ABC was first introduced by Dervis Karaboga in 2005 and inspired by the foraging behavior of honeybees [137]. It operates based on four steps: 1) Initialization (randomly generate different combinations of renewable sources as the initial population of bees). 2) Employed bee phase (each bee searches the vicinity of its location to find a better combination of facilities). 3) Onlooker bee phase (the optimum location based on the fitness function is shared with all bees). 4) Scout bee phase (search for new solutions in the search space and replace the worse locations with new ones) [42].

6.2.5. *Grey wolf optimization algorithm (GWO)*

The GWO is inspired by the social behavior of grey wolves in search of prey and was proposed in 2014 by Mirjalili et al. The GWO algorithm operates in four steps: 1) Searching for Prey (each wolf searches for the optimal solution, referred to as prey), 2) Encircling Prey (other wolves surround the wolf that found the optimal solution), 3) Attacking Prey (the encircling wolves then attack the prey by updating their positions toward the optimal solution), and 4) Updating the Hunting Position (the wolves' locations are updated based on their current location and the optimal solution found so far) [36,57].

6.2.6. *Flower pollination algorithm (FPA)*

The FPA is another heuristic algorithm introduced by Yang in 2012, inspired by the process of flower pollination. Fig. 38 presents the process of FPA for determining the optimum combination of sources, which includes four main stages: 1) Initialization: the locations of flowers are randomly generated across the solution space. Each location determines a specific combination of renewable sources. 2) Global pollination: some pollen is transferred between two flowers within a certain distance. 3) Local pollination: The flowers' positions are adjusted by a Gaussian distribution around their current position. 4) Update: updating the locations of flowers and their fitness values [51,211,212].

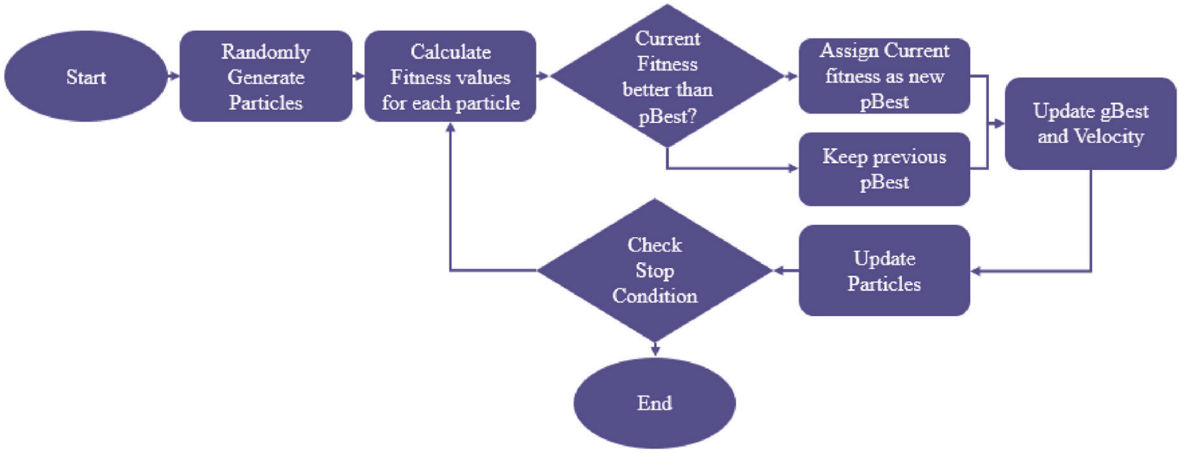


Fig. 35. PSO process [73].

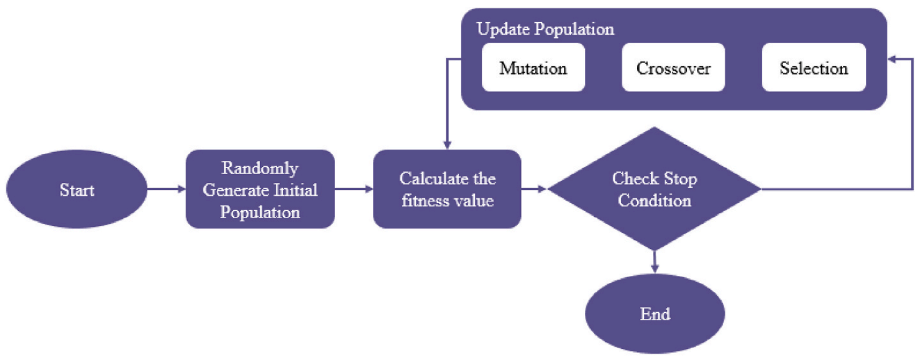


Fig. 36. GA process.

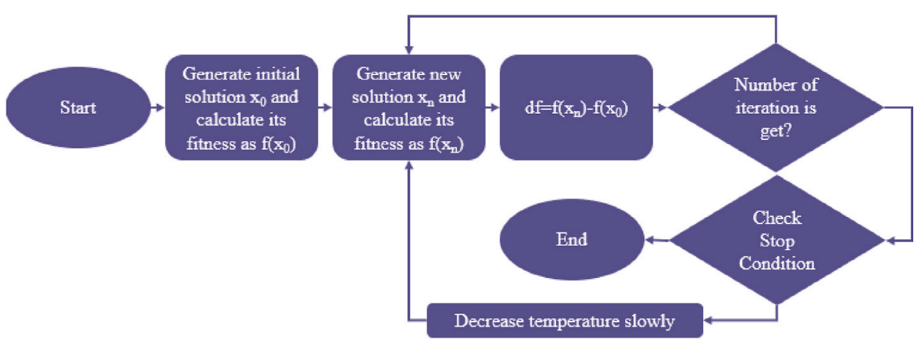


Fig. 37. SA process [48].

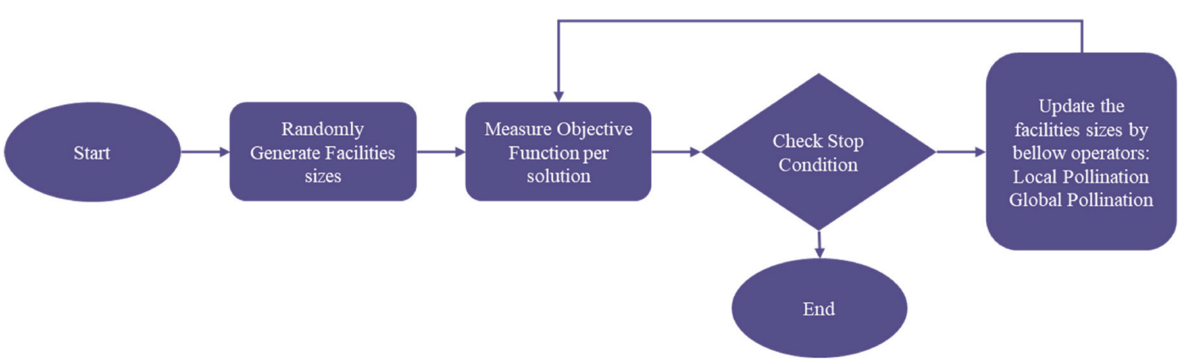


Fig. 38. FPA process.

6.3. Combined heuristic algorithms

Besides single heuristic algorithms, their combination is also used to reach a more appropriate solution. The algorithms can be combined in series, as shown in Fig. 39, or in parallel, as shown in Figs. 40 and 41. In parallel cases, the heuristic algorithms solve the problem separately and then share their results in each generation. In other cases, algorithms attempt to improve the results of another algorithm. Based on Fig. 39, PSO and SA-based combination models are the most commonly used in combined algorithms. Combined heuristic algorithms are also employed for multi-objective cases, with the combination of MPSO and NSGA-II being the most frequently used algorithm for solving such problems. Fig. 41 presents the combination of PSO and GA, which uses only the selection operator from GA and does not employ all the operators.

6.4. Software based

Various software solutions are available to identify the optimal mix of renewable energy sources, as demonstrated by several articles that have utilized the following programs. Among all the software, HOMER is the most frequently used due to its advantages.

6.4.1. Hybrid optimization of multiple energy resources (HOMER)

HOMER was developed by the National Renewable Energy Laboratory (NREL) to determine the optimal combination of energy sources based on the different parameters. Different energy sources such as solar, wind, hydro, and biomass can be defined by HOMER to determine the most cost-effective and reliable combination for the given location [78,125,194]. The optimum result is proposed based on predefined variables such as energy demand, resource availability, equipment costs, and performance characteristics. Evaluationg the environmental and financial impacts of changes in different parameters is a key feature of HOMER [23,76,78,91,96,125,130].

6.4.2. RETScreen

RETScreen was developed by the Canadian government to determine the optimum combination of renewable sources in terms of financial and performance metrics. RETScreen incorporates a wide range of meteorological information such as radiation rate and wind speed for various locations. Sensitivity analysis of different parameters on the objective functions and consideration of heat in addition to electricity are the main characteristics of RETScreen [215].

6.4.3. EnergyPLAN

EnergyPLAN is a free software tool developed by the Sustainable Energy Planning Research Group at Aalborg University in Denmark to determine the optimum combination of renewable sources. As various renewable energy sources, such as wind, solar, biomass, and hydro can be defined in EnergyPLAN, it can be used to determine the optimum combination of sources for various levels from individual buildings to a region. The impact of the different variables on generation rate and greenhouse gas emissions can be measured by EnergyPLAN [216].

6.5. Hybrid models

Besides the previous techniques to determine the optimum combination of renewable sources, hybrid models are also used in the literature. These models combine two or more different models to enhance the efficiency of the results. The most used hybrid models include the combination of Monte-Carlo Simulation (MCS) and heuristic algorithms. In such a model, due to the complexity of the system and the existence of some stochastic parameters, MCS is used to evaluate the fitness functions [39,217]. both used the combination of PSO and MCS as shown in Fig. 42.

7. Discussion and future direction

Combining PV with other sources of energy can achieve a reliable supply of energy even in areas far from the grid. The combination of PV with a wind turbine and a battery is a common approach used in the literature. The optimum combination problem can be divided into two different scenarios: grid-connected and off-grid. Energy flow management is important in the grid-connected scenario, where installing the battery plays a crucial role.

To solve the optimum combination problem, several factors should be considered as main decision variables: PV panels, wind turbines, or batteries with specific capacities, the optimum capacity of facilities, the area occupied by the facilities, and their types. In some cases, the angle of installation is also investigated.

Efficient flow management (such as charging the battery from the grid during off-peak times and using the saved energy during peak times) can reduce the generation cost by up to 57 %. Energy flow management also plays an important role in battery lifetime. In energy flow management, energy price and export limitation strategies are important and should considered in the modeling. Since energy flow management aims to sell over-generated energy at the highest price, the pricing system (TOU, CPP, and RTP) can impact the optimum capacity. Export limitation is preferred in some countries to increase grid stability. If the system cannot sell more than the export limitation, its efficiency may be lower, and as a consequence, energy costs may increase.

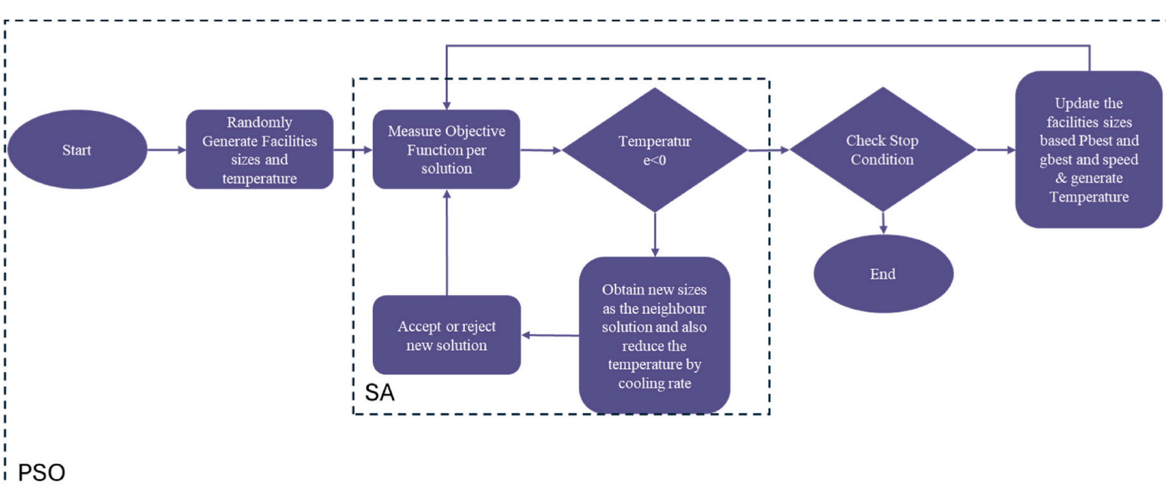


Fig. 39. Combination of PSO and SA [213].

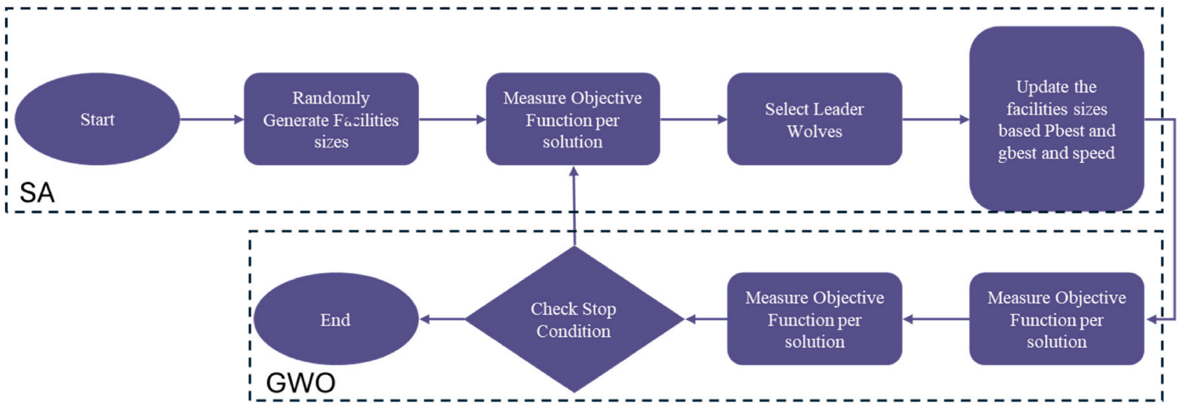


Fig. 40. A combination of GWO and SA [57].

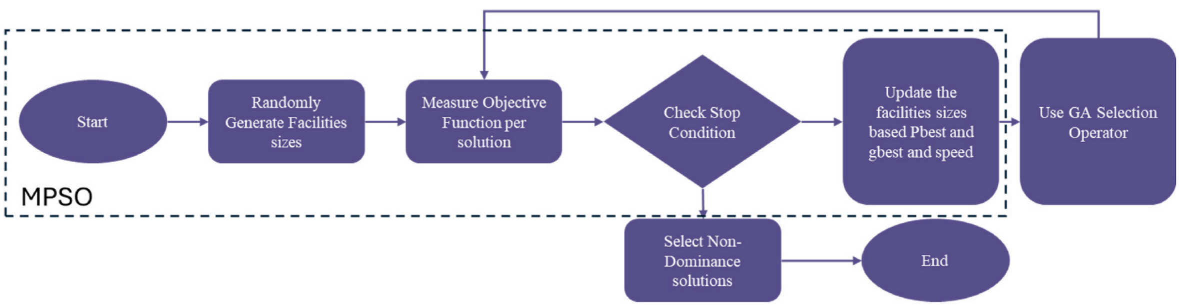


Fig. 41. Combination of MPSO and GA [214].

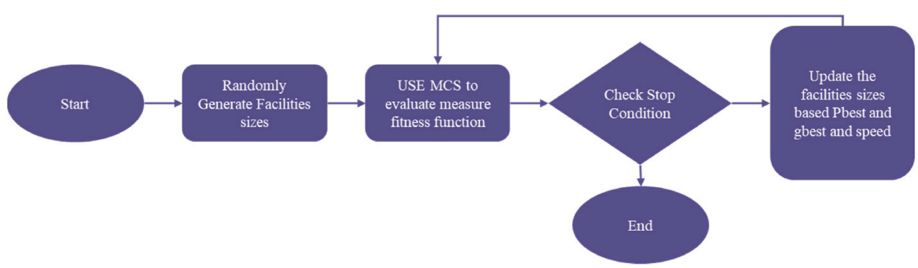


Fig. 42. Combination of PSO and MCS [39].

Among all the objective functions, which can be categorized into five groups: reliability, financial, environmental, social, and technical, the first two objectives are the most common. Reliability-related objective functions are mostly used in off-grid cases, while financial-related objective functions are predominantly considered in residential cases.

Based on the comprehensive review, the following future research directions are suggested.

- While many previous studies have used hourly time steps for predicting energy demand and generation, shorter time steps yield more accurate results, especially for designing more reliable off-grid systems.
- Due to significant fluctuations in energy demand and generation rates, these should be considered stochastic parameters rather than constant values.
- In off-grid problems, where there is no reserve source of energy, the demand spike points should be given a high weighting.
- The stochastic characteristics of generation rates are not well addressed.
- The optimum export time with flexible prices is neglected in the literature.
- The impact of natural events, such as blizzards, on the system life cycle has been overlooked in previous research.
- The role of export limitations, which are legislated in several countries, is often neglected in many articles.
- The cost imposed by energy shortages in off-grid problems is not adequately addressed in previous research.
- The effect of energy prices on the optimum size of systems is unclear in the literature.
- To minimize the energy cost, separate profiles for dispatchable and non-dispatchable demand should be considered.
- Uncertainty characteristic of facilities degradation should be considered in the modeling.

8. Conclusion

Renewable energy sources, often referred to as clean energy, have become the predominant choice for new installations worldwide. In 2022, renewables accounted for 83 % of all new energy installations globally, with PV systems making up 60 % of these renewable sources. The variable nature of PV output necessitates integration with other generation sources and storage solutions to enhance system reliability.

For this study, the PRISMA method was employed to select relevant papers, and a text-mining model was used to identify the criteria for comparison. These criteria include the type of grid connection, decision variables, objective functions, location types, and solving techniques.

Based on the results, for low and medium-demand scenarios, the PV/ES combination is most common, whereas, for high-demand scenarios, wind turbines are frequently added to the mix. In off-grid situations, DG serves as a backup to improve system reliability at minimal cost.

Financial considerations often dominate the planning process, leading to the widespread use of TAC, LOCE, and NPV as key metrics in the literature. However, in off-grid applications, reliability metrics are also crucial, either as part of the objective function or as constraints. When incorporating DGs, environmental and technical factors are evaluated within the objective frameworks.

To address the complexity of these systems, multi-objective optimization techniques are commonly employed, yielding efficient solution frontiers. Heuristic algorithms, particularly PSO and GA, are favored for their problem-solving efficacy. When combined algorithms are necessary, SA, PSO, and HS-based models are preferred. Some articles also used software-based techniques to solve the problem, with HOMER being the most used compared to other software tools. As the scope of this research is limited to the mathematical model for decision making on the optimum combination of PV-based sources, other areas like technical issues can be evaluated in future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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