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Rural electrification: An overview of optimization methods

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ABSTRACT

In order to provide "affordable, reliable, sustainable and modern energy for all" by 2030 under Sustainable Development Goal 7 (SDG7), rural electrification needs significant progress as the majority of people without access to electricity reside in rural areas. Optimization methods can play a critical role in this progress, providing an analytical framework to achieve a variety of economic, social, and environmental objectives subject to budget, resources, local demographics and other constraints. This review paper presents the first overview of optimization-based solution methodologies developed or applied for rural electrification. Based on our review, we first propose four archetype problems for rural electrification, namely (i) optimal system configuration and unit sizing, (ii) optimal power dispatch strategy, (iii) optimal technology choice, and (iv) optimal network design. We discuss each problem type, and provide a systematic classification based on the problem objective, proposed solution methodology, components, scale, region as well as their relationship to the different SDG7 components. We reveal research gaps and open questions for future studies for energy researchers and aim to draw the attention of the optimization community to the challenging and unique problems that need urgent attention in this critical area.

1. Introduction

1.1. Motivation

As countries move towards achieving Sustainable Development Goal 7 (SDG7)- access to "affordable, reliable, sustainable and modern energy for all" [1] - they will have to pay significant attention to rural areas. While the number of people without electricity access dropped from 1 billion in 2016 to a record-low 770 million in 2019, progress has been considerably slower in rural areas. The global electricity access rate in urban areas (approximately 97%) is larger than in rural areas (82%) [2], implying that 84% of all people without access to electricity reside in rural areas. In several low-income and lower-middle-income countries (LMICs), inequalities between rural and urban electrification rates are as high as an order of magnitude [3]. Rural and sparsely populated areas tend to wait the longest to be served by electrification technologies [4–6], despite off-grid electrification projects being likely to be successfully commissioned once they are planned [7]. Rural households in LMICs can be difficult to reach, and initial demand is low, complicating the business case of electrifying them [8]. There are also remote or rural migratory populations that are hard to locate and pose additional challenges for creating electricity connections. The COVID 19-pandemic is further complicating reaching universal electricity access due to its predicted decelerating effect on the pace of electrification [9]. Rural electrification in accordance with SDG7 may thus require new and concerted strategies tailored to context-specific structures and demographics [10,11].

It is widely accepted that accurate and rigorous electrification planning approaches are required to optimally use the limited resources to achieve SDG7 by 2030 [12–14]. Critically, in addition to providing access to modern energy, SDG7 explicitly sets out three further aims to do so, namely in an affordable, reliable and sustainable fashion. Many extant rural electrification planning approaches are based on simple cost comparisons for different electrification options for high geospatial resolutions [15–19], but are greatly limited in technical detail and in engaging with the many links rural electrification has for sustainable development [20]. By contrast, mathematical optimization provides a formal framework capable of simultaneously and explicitly considering cost, reliability and sustainable technology choice for electrification, while integrating a variety of different economic, social and environmental objective functions and constraints. Achieving SDG7 will

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List of Abbreviations

ABC	Artificial Bee Colony Algorithm
Aff.	Affordability
BO-MILP	Bi-Objective Mixed Integer Linear Programming
DP	Dynamic Programming
FA	Firefly Algorithm
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GC	Grid-Connected
GD	Gradient Descent
GSA	Gravitational Search Algorithm
HS	Harmony Search
HDI	Human Development Index
ISO	Implicit Stochastic Optimization
LP	Linear Programming
LLP	Loss of Load Probability
LPSP	Loss of Power Supply Probability
LMICs	Low-income and lower-middle-income countries
MILP	Mixed Integer Linear Programming
MCS	Monte Carlo Simulation
MFO	Moth-flame Optimization
MO-MILP	Multi-Objective Mixed Integer Linear Programming
MO-PSO	Multi-Objective Particle Swarm Optimization
MO-SSO	Multi-Objective Salp Swarm Optimization
MADE	Mutation Adaptive Differential Evolution
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
NLP	Non-linear Programming
PESA-II	Pareto Envelope-based Selection Algorithm
PSO	Particle Swarm Optimization
RE	Renewable Energy
Rel.	Reliability
SA	Simulated Annealing
SDG	Sustainable Development Goals
SPEA-II	Strength Pareto Evolutionary Algorithm-II
SSO	Salp Swarm Algorithm
Sust.	Sustainability
TLBO	Teaching–Learning Based Optimization
Unc.	Uncertainty

arguably be most difficult in rural areas due to the large difference in per capita cost of electrification in these two settings, and the already existing considerable gap between urban and rural electrification in most African countries [3,21]. Hence, there is a need to design custom-made analytical tools to ensure that scarce resources for rural electrification are deployed optimally. Critically, optimization models are flexible enough to be tailored towards the key sub-categories of SDG7, namely optimizing for affordability, reliability, sustainability and access for all. Indeed, the extant literature can be mapped against these SDG7 sub-goals, providing decision makers crucial insights on the different, and at times conflicting sub-goals of SDG7 (see Section 2). Furthermore, optimization models can simultaneously consider multiple objective functions. When applied to different SDGs, or different SDG sub-goals, this enables them to provide key insights between synergies and trade-offs of different SDGs. Hence, optimization methods have the potential to assume a critical role in rural electrification planning, which integrates various links and aspects of sustainable development.

Several papers have focused on reviewing electrification planning in developing countries but have not focused specifically on optimization approaches. In a recent study, Ciller et al. [22] review the large-scale planning tools developed for solving energy-access problems. Some studies provide an overview of the literature based on the type of energy source used as in [23] for biomass-based hybrid renewable energy systems [24], for portable solar photovoltaic (PV) systems [25], and for the design of wind-PV systems [26]. Mandelli et al. [13] provide a comprehensive review of off-grid approaches in general, while the recent work by Ortega-Arriaga et al. [27] reviews and compares grid and off-grid electrification options and their respective socio-economic and environmental impacts. Riva et al. [28] discuss demand forecast in remote locations and long-term energy planning with a modeling perspective. Trotter et al. [12] review the electricity planning studies in a broad sense focusing on sub-Saharan Africa. Akikur et al. [29] present a comparative review for standalone and hybrid solar energy systems, and Izadyar et al. [30] review the theoretical and technical potential of renewable energy sources for remote areas. Several review papers focus on the studies related to off-grid power systems' planning and operations in isolated regions [31–34]. Kumar et al. [35] and Rojas-Zerpa and Yusta [36] review multi-criteria decision-making methods (MCDM) for renewable energy development and electric supply planning for rural areas, respectively. Some other review papers in the literature have discussed the role of modeling and optimization for energy systems in general, not specifically with a rural electrification perspective. In a recent study, Ridha et al. [37] survey multi-objective optimization and MCDM methods for the optimal design of standalone PV systems. Erinc and Uzunoglu et al. [38] review the optimization approaches for designing hybrid renewable energy systems with great detail on genetic algorithm-based approaches. Siddaiah and Saini [39] discuss different configurations of hybrid renewable energy systems and the optimization approaches used for designing these systems, specifically for off-grid systems. Bazmi and Zahedi [40] review the studies up to 2011, optimizing the power generation and supply side.

Hence, to the best of our knowledge, no literature review exists that analyzes research on the analytical foundation and methodology for optimization problems in rural electrification. This paper fills this gap in the literature by reviewing the relevant literature that proposes an optimization-based solution for rural electrification. Rural electrification is often the bottleneck in countries reaching universal electricity access. Thus, it requires special attention from the research community.

1.2. Review methodology

We used the Web of Science database as the primary source for the review process. To identify the relevant studies, we searched for "electrification" in combination with optimization-related keywords, namely "optim*", "least-cost" and "energy planning". In the review process, we focused on English-speaking journal articles, and included all papers published between January 2000 and October 2021. To maximize the coverage, in addition, we also included additional papers based on the identified studies' reference lists and on our previous research experience. After a preliminary evaluation of 491 articles by title and abstract, we identified 111 papers to review in detail and classify according to the problem category, implemented renewable technologies, solution methodology, region, scale and SDG relevance. Due to their limits in technical detail and flexibility, we excluded studies that use pre-defined electricity planning software. We refer readers to [14] for a comprehensive review on the large-scale planning tools developed for the energy access problem or to [41] for the studies which use HOMER for optimal planning of hybrid energy systems.

1.3. Contributions and organization of the paper

The specific contributions of this review paper are as follows: (i) We present the first review paper on the optimization approaches developed or applied for rural electrification problems towards the different aspects of SDG7. (ii) We provide a systematic classification of the rural electrification problems based on the problem objective, proposed solution methodology, and components, scale and the regions of the systems considered. (iii) We identify research gaps and open questions for future studies for energy researchers and aim to draw the attention of the optimization community to the challenging and exciting problems yet to be addressed in this critical area.

The rest of the paper is organized as follows: Section 2 provides the classification of the rural electrification studies based on four different problem types and presents a temporal and regional overview. Sections 3–6 provide a deep-dive into each of the four rural electrification problem types, respectively, with a focus on the different mathematical techniques used to solve them. Section 7 draws on the findings of the review to conclude the paper by distilling key research gaps.

2. Classifications of the rural electrification problem

The detailed analysis of the studies informed us to propose a categorization of rural electrification problems into four problem types: (i) optimal system configuration and unit sizing, (ii) optimal power dispatch strategy, (iii) optimal technology choice, and (iv) optimal network design. First, the optimal system configuration and unit sizing problem involves selecting the types of energy resources and sizing energy system components. Second, the optimal power dispatch strategy problem focuses on the scheduling of operational activities, including the electricity generation and the power flow between components. Third, the optimal technology choice problem chooses different generation technologies and types of electrification technologies (on-grid, off-grid, embedded) subject to a given set of objective functions. Fourth, optimal network design models attempt to find local network configurations that meet the case-specific objective criteria. Critically, in serving different purposes of rural electrification, these four types of problems differ in their capability to address different aspects of SDG7, namely affordability, reliability and sustainability. While they all maximize affordability due to their commonly inherent cost minimization approaches, the optimal system configuration problem as well as the power dispatch problem are able to explicitly model reliability by modeling minimum reserve margins, different losses, failures and associated power outage risks. The optimal technology choice model can be designed to minimize carbon emissions from the system to improve the environmental sustainability of rural electrification. Finally, the optimal network design model can consider reliability by modeling power dynamics and voltage drop risks depending on distance from transformers which was recently found to be a critical and understudied issue of rural electrification [42–44]. During the review process, we also encountered two articles on the maintenance system structures for rural electrification. However, as the number of studies that fall into this category remained quite limited, instead of creating a section to discuss these studies, we refer the interested readers to [45] and [46] and the other references therein.

Fig. 1a presents a Venn diagram with the number of studies that fall under these four categories. The majority of the reviewed studies address a single problem type. Nevertheless, some studies integrate two different problem types into one optimization framework as visible in the intersection areas of the diagram, but we did not identify a single paper that combines three or all four problem types. For example, in terms of optimal system configuration and unit sizing problems and optimal power dispatch strategy problems, once the optimal system configuration is identified, energy planners attempt to optimize the dispatch strategy to minimize operational costs in the latter one. Our review identifies several studies that integrate these model types [47–55].

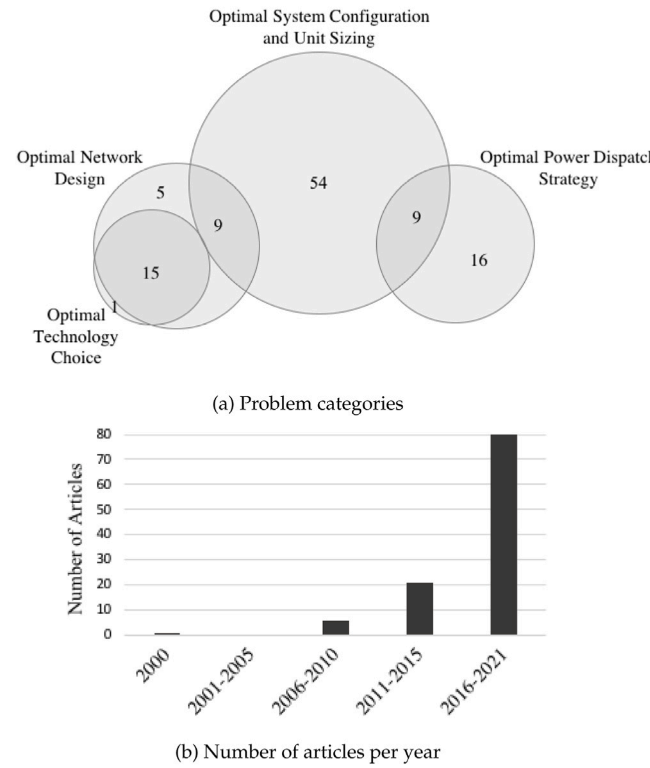


Fig. 1. Distribution of reviewed articles into (a) problem categories and (b) year of publication.

Furthermore, since the optimal technology choice problems involve grid option as a technology choice, this problem category can also include optimal network design. Similarly, some mini-grid applications may involve identifying the types of energy generators used in the system and network between generators and final consumers [56–63]. While we acknowledge that multiple papers can address more than one problem type, it should be noted that for the sake of our subsequent problem-specific deep-dive sections, we assign each of these papers to the problem category where it provided the highest degree of modeling detail, respectively.

Fig. 1b depicts the number of studies in this literature review for the period between January 2000 and October 2021. The interest in the rural electrification problem has exponentially increased from 2006 to the present. However, the upward trend between 2015 to 2021 has become more significant after the UN's Agenda 2030 was adopted in 2015, which unlike the UN Millennium Development Goals, chose to elevate universal access to modern energy as a goal in itself. The time trend for each problem type is provided in Fig. 2. The temporal development of optimal technology choice and optimal network design studies reflects the overall trend of the literature. While the distribution of optimal technology choice and optimal network design studies remained stable in the periods 2011–2015 and 2016–2021, the number of articles that fall into optimal power dispatch strategy and optimal system configuration and unit sizing categories increased significantly in 2016–2021.

Fig. 3 illustrates the geographical distribution of the reviewed articles and the electricity access rate of the respective countries in 2018 [64]. A total of 107 among the 111 articles reviewed in this paper conduct a case study on real-world settlements in developing countries to evaluate the performance of the proposed methodology. The optimization frameworks proposed in these 107 studies are applied to 43 countries belonging to 4 different continents. Approximately 76% the studies reviewed in this analysis occur in Asia (42 studies) or Africa (40 studies) (see Fig. 4a). The studies focusing on the rural

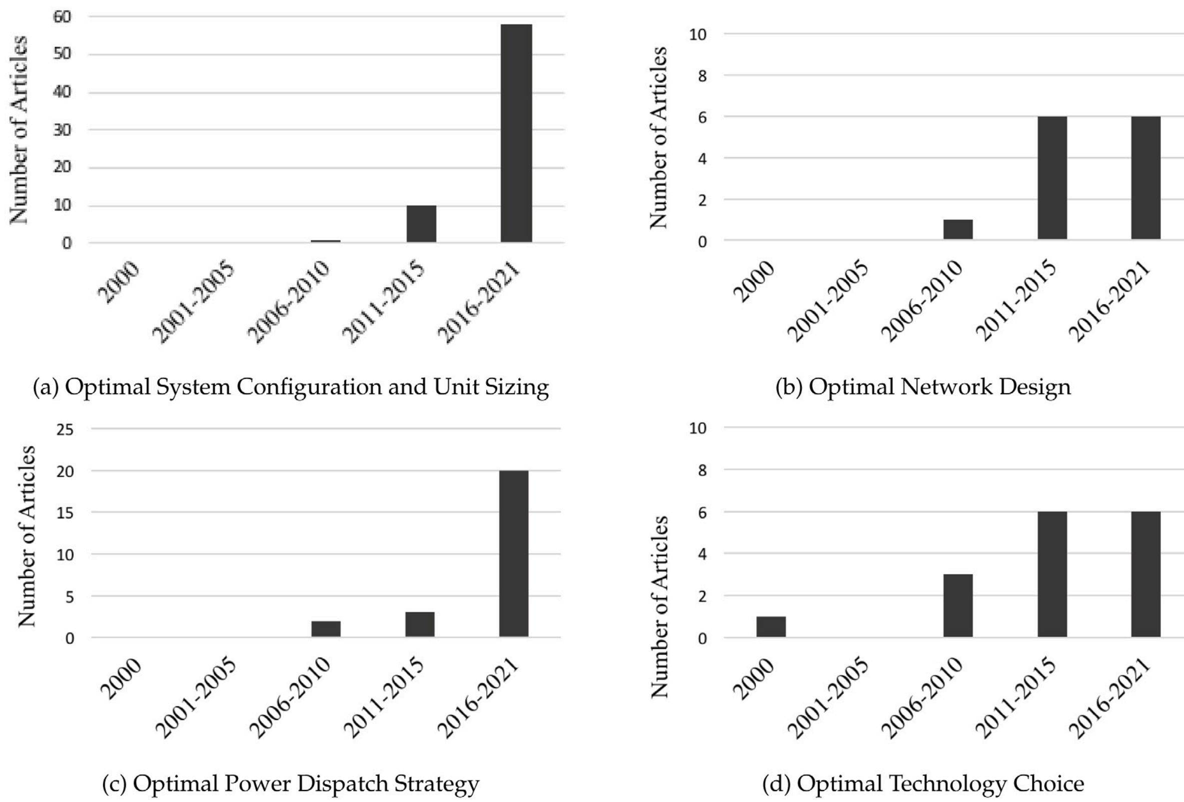


Fig. 2. Number of reviewed articles per year for each problem type.

electrification projects in Central and South America, on the other hand, constitute approximately 18% of the identified articles. Although the primary motivation of the rural electrification studies is to provide electricity access to the areas with low electrification rates, Fig. 3 indicates that only 15%of the articles address the countries having electrification rates below 50%. For instance, while we did not identify a single optimization-based rural electrification study for any of the four countries with the lowest electricity access rates in the world (namely Chad, Burundi, South Sudan and Malawi) [64], we identified 17 studies for the rural electrification of India with the access rate exceeded 95% in 2018. Thus, our analysis reveals a mismatch between the electrification rates and the number of optimization studies, highlighting a need for more studies in countries with low access rates.

Fig. 4b demonstrates the classification of the articles based on the geographical region and the rural electrification problem they addressed. The geographical distribution of the articles on the optimal network design and optimal power dispatch strategy have similar features. The studies identified for the Asian and African countries correspond to more than 50% of the studies examined under these two problem types. Although studies on African countries dominate the rural electrification studies, Asia is the primary focus in the optimal system configuration and unit sizing problems. Comparatively, there are a limited amount of studies addressing the optimal technology choice problem of rural electrification problem, with most studies focused on Africa.

In addition to the countries addressed in the reviewed studies, the geographical scale of the case studies is another aspect to evaluate. The choice of geographical scale varies based on the scope of the electrification projects or the availability of the data sources. In this literature review, we observed that the geographical scale of the electricity planning problem could be classified into two distinct categories, namely national and subnational scale problems. The subnational scale problems involve the electricity planning of individual households or smaller settlement clusters such as villages, counties, or states. The majority of the system configuration, power dispatch strategy, and network design and facility location problems, 86%, 76%, and 85% of the reviewed articles, respectively, address the village scale electrification projects. As opposed to the other rural electrification problems, most of the existing work on the optimal technology choice problem focuses on the national-scale analysis, especially in African countries.

We group the optimization approaches proposed in the reviewed studies into three categories: optimization models, heuristics, and metaheuristics. Although optimization models are extensively used to obtain the optimal energy solutions and considered as exact approaches, the literature is also prone to heuristics and metaheuristics to solve large-scale or non-differentiable optimization problems. This paper refers to specific and problem-dependent methods expected to find quick solutions for large-scale problems as heuristics. Metaheuristics are, on the other hand, referred to as high-level problem-independent algorithmic frameworks that can be applied to a wide range of problems. Both heuristic and metaheuristic approaches are expected to find "acceptable" solutions in a "reasonable" time frame. While heuristics and metaheuristics provide approximate solutions for which the solution quality cannot be guaranteed, another category of the optimization methods would be approximation algorithms. Approximation algorithms can provide proven bounds on the solution quality. However, to our knowledge, there does not exist any approximation algorithm developed for rural electrification studies. Fig. 5 illustrates the distribution of the reviewed papers using optimization models, heuristic algorithms, or metaheuristic algorithms to propose a potential solution. Table 1 provides a detailed list of the approaches. In the following sections, we elaborate on the optimization methods proposed for each problem type identified under rural electrification.

3. Optimal system configuration and unit sizing problem

In this section, we analyze the papers which focus on the optimal system configuration and unit sizing aspect of rural electrification. To

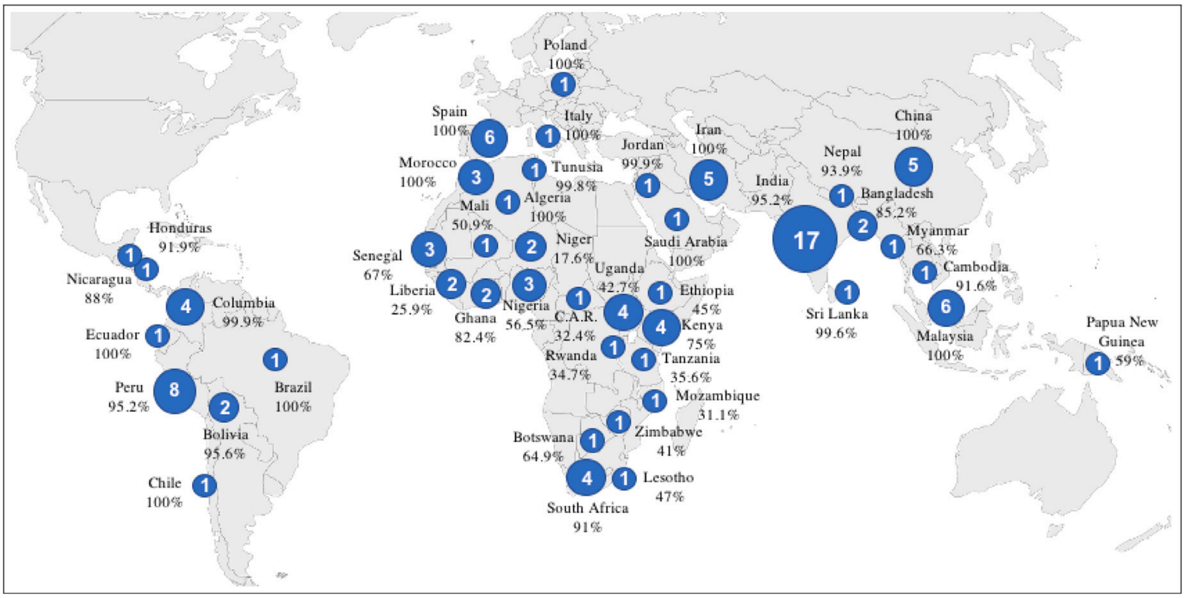
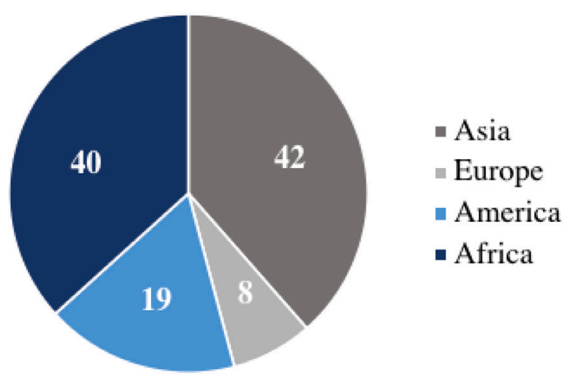
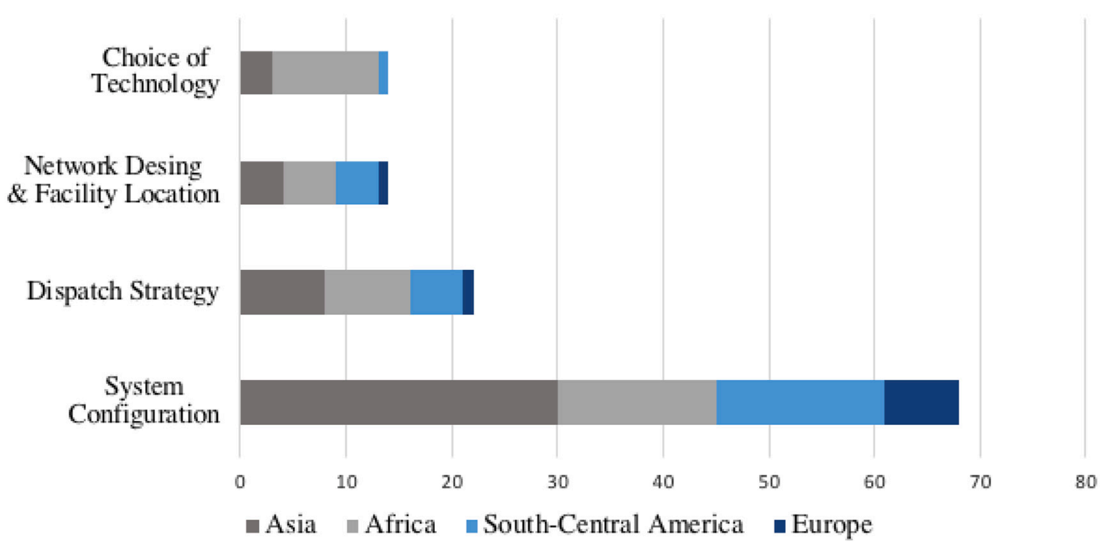


Fig. 3. Distribution map of the reviewed articles (blue circles) and associated electrification rates (percentages).
Source: Reported by the World Bank [64]



(a) Distribution of the reviewed articles by region



(b) Classification of the articles based on rural electrification problem types

Fig. 4. Classification of the reviewed studies by (a) region and (b) rural electrification problem type.

Table 1
Summary of the optimization frameworks proposed in the reviewed articles.

Solution methodology	Optimization technique	References
Optimization models	LP	[48,49,55,56,65–76]
	MILP	[21,45,46,54,57–59,61,77–95]
	DP	[96]
	NLP	[97–99]
	Others	[5]
Heuristics	MST-based	[43,100–108]
	Others	[60,62,109–112],
Metaheuristics	GA	[47,50,51,53,63,113–129]
	PSO	[52,130–141]
	HS	[136,142–146]
	ABC	[143]
	FA	[143]
	MFO	[147]
	Others	[148–153]

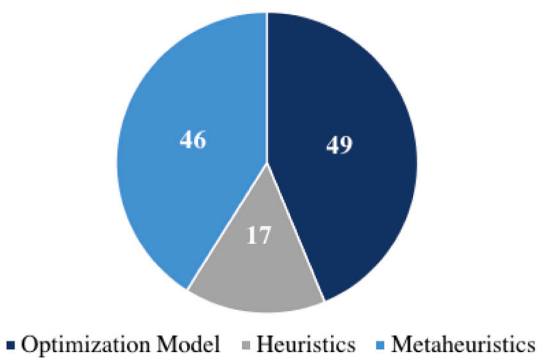


Fig. 5. Distribution of the optimization approaches proposed in the reviewed articles.

provide electricity to rural areas, the choice of energy sources plays an important role prior to implementing hybrid systems. The sizing of system components is also a critical decision for the energy planners to achieve the maximum efficiency, especially where intermittent renewable energy sources are considered. In Table 2, we summarize the reviewed articles in terms of optimization methodology, criteria, system configuration and provide the details of the case studies with the geographical scale of optimization. We also indicate the different aspects of SDG7, including affordability, sustainability and reliability aspects, along with the other SDGs that have been addressed in the reviewed articles. Notably, we did not find a single optimization study on system configuration and sizing that did not consider at least one type of renewable energy-based technology for rural electrification, considering integrating renewable energy sources and investigating the implementation of hybrid systems for rural electrification. This focus on renewable energy technologies is motivated by their ability to address the energy deficit in rural areas given their decentral abundance. Isolated and off-grid hybrid electrification options are often considered particularly suitable and practical for remote regions since they do not require the construction of a power network [154], and have been found to be the cheapest off-grid electrification option in many contexts [12].

Classical optimization techniques have been widely preferred for the hybrid renewable energy systems design and the optimal system configuration problems. Some examples of the classical optimization techniques that have been implemented in the reviewed studies include linear programming (LP) [55,56,65,72,74,75], mixed integer linear programming (MILP) [48,54,57–59,61,77,84–86,88,89,93,95,155] and implicit stochastic optimization (ISO) [76]. Besides these classical methods, heuristic or metaheuristic approaches can be effective in obtaining approximate solutions for larger instances in less computational time. These methods are especially convenient to deal with the non-convex or discontinuous problems for which the classical techniques become impractical due to the complex structure of the problem.

We encounter numerous studies in the literature implementing heuristic or metaheuristic algorithms to optimize the sizing of the components in hybrid systems. In particular, the metaheuristic approaches that imitate natural occurrences using biological principles and the concept of collective intelligence have been frequently utilized in this type of optimization problem. The Genetic Algorithm (GA) is considered one of the most widely preferred optimization techniques to solve system configuration problems [50,51,63,113,115–120,122–125,128,129]. The working principle of the Genetic Algorithm relies on the natural selection process including cross-over and mutation operators [156]. Particle Swarm Optimization (PSO), on the other hand, imitates the social behavior of the organisms in a bird flock or fish school [157]. This method is frequently utilized in optimal system configuration and unit sizing studies [52,130–141]. In this optimization technique, each particle denotes a potential solution. The final output is obtained by updating the generations at each iteration. However, unlike the Genetic Algorithm, Particle Swarm Optimization does not utilize the cross-over and mutation operators for the evolution of the generations [158]. Harmony Search (HS) is another approach used to obtain the optimal system configuration and unit sizing [136,142–146]. This technique is inspired by the improvisation of the harmony of musical instruments [159]. Artificial Bee Colony Algorithm (ABC) represents the intelligent behavior of the honeybee swarm while searching for nectar [160], and this approach is implemented for the optimization of the system configuration in [143]. Similarly, [143] use the Firefly Algorithm (FA), which is inspired by the flashing pattern of the fireflies for signal transfer.

In line with this, other examples of metaheuristic algorithms that have been attempted to solve optimal system configuration and unit sizing problems are salp swarm algorithm (SSO) [150], steady ϵ-state evolutionary algorithm [149], moth-flame optimization (MFO) [147], teaching–learning based optimization (TLBO) algorithm [152], flower pollination algorithm (FPA) [143], Pareto envelope-based selection algorithm (PESA-II) [151] and mutation adaptive differential evolution (MADE) [148]. Apart from the metaheuristic methods, some studies develop problem-specific heuristic approaches as in [60,62,109,111].

Generally, the optimization frameworks for sizing problems aim to obtain an appropriate system configuration while minimizing the overall cost of electrification. In order to obtain a feasible configuration, supply–demand equalities, generation capacity and power balance constraints are ensured. However, as a result of renewable energy integration, some studies may also examine reliability, renewable energy fraction, and environmental impacts of the system. The system's reliability is an important performance measure for hybrid systems that include intermittent renewable energy sources. For this purpose, some researchers tend to examine Loss of Load Probability (LLP) and Loss of Power Supply Probability (LPSP) indices in addition to the life-cycle cost of the system [123,128,129,131–134,144–146,148,150,151]. Similarly, two representative metrics are commonly used, namely carbon

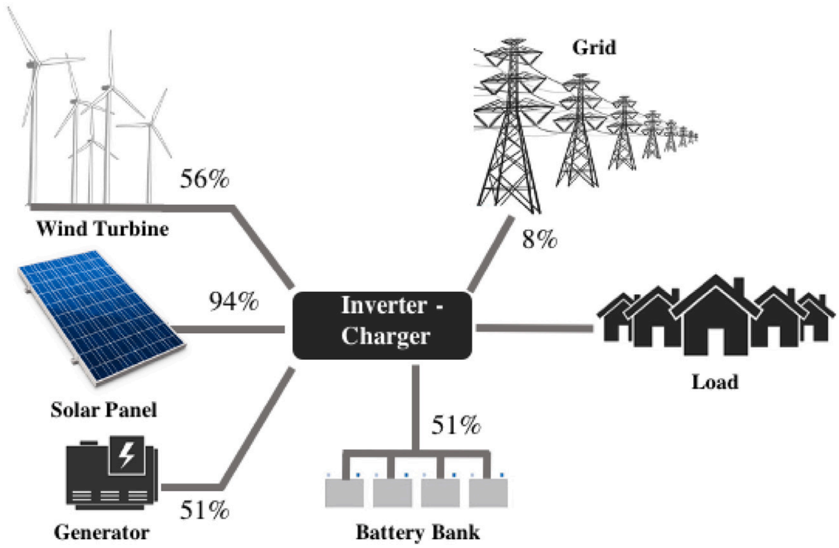


Fig. 6. An illustration of hybrid renewable energy systems. The numbers on the figure represent the percentage of the studies including the corresponding system component.

dioxide and greenhouse gas emissions, to observe the environmental impact of hybrid systems. [53,117,125,130] use these metrics and aim to promote the integration of renewable technologies to reduce the adverse effects of conventional sources on the environment.

Renewable energy technologies exhibit stochastic behaviors by nature, and this stochastic inclination has a significant impact on the performance of the system components. The electricity generation of hybrid systems that are neither connected to the main grid nor having backup generators is especially subject to uncertainty. Although the stochastic optimization methods could be beneficial to address the uncertainties involved and provide more accurate outputs, such studies considering stochasticity are uncommon in the literature, most likely due to their computational complexity. Among 63 studies summarized in Table 2, only 14.3% of them presents an optimization framework in accordance with the stochastic nature of renewable energy sources [48, 54,63,76,78,123,124].

On the other hand, the majority of the studies prefer combining multiple renewable energy sources, using diesel generators or battery storage to reduce the intermittency instead of committing to a single renewable source. For this purpose, the solar generation systems are generally combined with wind turbines and diesel generators. As shown in Fig. 6, 94% of the studies include solar panels as a technology option, while 56% include wind turbines, and 51% include a backup generator to the system. Hydropower and biomass are used in nearly 14% of the reviewed papers, and approximately 8% of the studies have biogas options. Around 8% of the studies reviewed in this section consider a grid-connected system to compensate for the intermittency of renewable energy sources, and 51% use a battery bank to provide a better service. In [132,152] optimization frameworks for grid-connected system configurations are presented and in [65,74,130] optimal sizing approaches for both grid-connected and isolated energy systems are provided.

The optimization frameworks provided in this section are implemented for real-life instances from a large number of countries on four different continents. In Table 2, we provide details of case studies from Asia, Africa, Europe, and South-Central America. Note that most of the case studies are performed for the countries in South Asia and South-Central America. The case studies utilize aggregated data for counties, small villages, or high-resolution data for individual consumers. However, the geographical scope of the optimal sizing studies generally covers smaller settlements such as rural villages. As we can observe in Table 2, approximately 90% of the case studies consider the village-level data.

Finally, Table 2 demonstrates that affordability and sustainability aspects of the SDG7 are frequently addressed as the optimization criteria is generally to minimize the total investment cost and the systems are heavily designed based on renewable sources. Reliability aspect is also considered in some of the papers by defining an upper bound on the loss of power supply probabilities as in [119,122,142]. In addition to SDG7, some studies could also refer to SDG1 (No Poverty), SDG8 (Decent Work and Sustainable Growth) and SDG13 (Climate Action) implicitly, by promoting the integration of low-carbon renewable energy resources [125,130] or maximizing the job creation factor [144] or human development index [50] in the objective function.

4. Optimal power dispatch problem

The economic viability of rural electrification, especially where decentralized hybrid renewable energy systems are considered, is strongly dependent on the operational costs which arise from the daily activities during electricity generation. Moreover, the allocation of energy resources and scheduling of the power flow between the generation points and final consumers significantly impact the reliability of the hybrid energy systems that involve various energy sources. Hence, to provide affordable and reliable electricity to the consumers living in rural areas, scheduling the operational activities and identifying the optimal power dispatch strategy constitute a significant part of rural electrification planning. In this section, we summarize the articles that focus on optimizing associated control strategies, including the scheduling of power flows and electricity generation in the systems. In Table 3, we provide further details in terms of the optimization framework, electricity generation technologies used in hybrid systems, the case studies on real-life instances, and the key attributes of SDG7 and the other sustainable development goals addressed in the studies.

Classical optimization techniques have been widely deployed for optimizing operational activities of hybrid renewable energy systems. More than 60% of the studies reviewed in this section (see Table 3) use linear programming to obtain the optimal operational strategy as in [49,55,66–70,73]. Some studies propose dynamic programming approach [96] and mixed-integer linear programming formulations [48, 78,80,82,90] for the solution of this problem. Evolutionary algorithms have also been used frequently for this problem category such as genetic algorithm [47,50,51,53,121], non-dominated sorting genetic algorithm-II [126,127] and particle swarm optimization [52]. Different from the previous evolutionary algorithms, [98] presents an optimization framework using the interior-point method to solve a large-scale non-linear optimization problem.

Table 2
Optimal system configuration and unit sizing.

Article	Heuristics and metaheuristics	Model	Objective	Unc.	GC	PV	Wind	Diesel	Hydro	Biomass	Biogas	Battery	Country	Scale	SDG-7			Other
															Aff.	Sust.	Rel.	SDGs
Bala & Siddique (2009) [47]	GA		Cost	–	–	✓	–	✓	–	–	–	✓	Bangladesh	Village	✓	✓	–	–
Bilal et al. (2010) [129]	GA		Cost, LPSP	–	–	✓	✓	–	–	–	–	✓	Senegal	Village	✓	✓	✓	–
Perera et al. (2013) [149]	Steady ε–State evolutionary algorithm		Cost, GHG emission	–	–	✓	✓	–	–	–	–	–	Sri Lanka	Village	✓	✓	–	SDG13
Borhanazad et al. (2014) [131]	MO-PSO		Cost, LPSP	–	–	✓	✓	✓	–	–	–	✓	Iran	Village	✓	✓	✓	–
Domenech et al. (2015) [85]		MILP	Cost	–	–	✓	✓	–	–	–	–	–	Peru	Village	✓	✓	✓	–
Gonzalez et al. (2015) [115]	GA		Cost	–	–	✓	✓	–	–	–	–	–	Spain	Village	✓	✓	–	–
Gonzalez et al. (2015) [116]	GA		Cost	–	–	✓	✓	–	–	✓	–	–	Spain	Village	✓	✓	–	–
Ranaboldo et al. (2015) [111]	Greedy heuristic		Cost	–	–	✓	✓	–	–	–	–	–	Nicaragua	Village	✓	✓	✓	–
Cristobal-Monreal & Dufo-Lopez (2016) [51]	MOEA, GA		Cost	–	–	✓	–	✓	–	–	–	✓	Central African Republic	House-hold	✓	✓	–	–
Dufo-Lopez et al. (2016) [50]	MOEA, GA		Cost, HDI, job creation	–	–	✓	✓	✓	–	–	–	✓	Algeria	Village	✓	✓	–	SDG1, SDG8
Dufo-Lopez et al. (2016) [124]	GA, MCS		Cost	✓	–	✓	✓	✓	–	–	–	✓	Spain	Village	✓	✓	✓	–
Ghavidel et al. (2016) [153]	GSA		Cost	–	–	✓	–	✓	–	–	–	✓	Nigeria	Village	✓	✓	–	–
Gonzalez et al. (2016) [117]	GA		Cost, CO2 emission	–	–	✓	✓	–	–	✓	–	–	Spain	Village	✓	✓	–	SDG13
Kanyarusoke et al. (2016) [86]		MILP	Cost	–	–	✓	–	–	–	–	–	–	Sub-Saharan Africa	House-hold	✓	✓	–	–
Rajanna & Saini (2016) [119]	GA		Cost	–	–	✓	✓	–	✓	✓	✓	–	India	Village	✓	✓	✓	–
Sigarchian et al. (2016) [52]	PSO		Cost	–	–	✓	–	✓	–	–	–	✓	Lesotho	Village	✓	✓	–	–
Chauhan & Saini (2017) [142]	Discrete HS		Cost	–	–	✓	✓	–	✓	✓	✓	–	India	Village	✓	✓	✓	–
Homayouni et al. (2017) [139]	PSO		Cost	–	–	✓	–	✓	–	–	–	✓	Iran	House-hold	✓	✓	✓	–
Kocaman & Modi (2017) [78]		MILP	Cost	✓	–	✓	–	✓	–	–	–	–	India	Multiple villages	✓	✓	–	–
Nasir et al. (2017) [75]		LP	Cost	–	–	✓	–	–	–	–	–	–	India	Village	✓	✓	✓	–
Ruiz-Alvarez et al. (2017) [72]		LP	Cost	–	–	✓	✓	✓	–	–	–	✓	Colombia	Village	✓	✓	✓	–
Sundaramoor-thy (2017) [74]		LP	Cost	–	✓/-	✓	✓	–	✓	✓	–	–	India	Village	✓	✓	✓	–
Eteiba et al. (2018) [143]	FPA, HS, ABC, FA		Cost	–	–	✓	–	–	–	✓	–	–	Egypt	Village	✓	✓	✓	–
Huang et al. (2018) [118]	GA		Cost	–	–	✓	✓	–	–	–	–	–	China	Village	✓	✓	✓	–
Patel & Singal (2018) [140]	PSO		Cost	–	–	✓	✓	–	–	✓	✓	–	India	Village	✓	✓	✓	–

(*continued on next page*)

Table 2 (*continued*).

Article	Heuristics and metaheuristics	Model	Objective	Unc.	GC	PV	Wind	Diesel	Hydro	Biomass	Biogas	Battery	Country	Scale	SDG-7			Other
															Aff.	Sust.	Rel.	SDGs
Roberts et al. (2018) [123]	GA		Cost, LPSP	✓	–	✓	✓	✓	–	–	–	✓	Brazil	Village	✓	✓	✓	–
Abuzeid et al. (2019) [137]	PSO		Cost	–	–	✓	✓	✓	–	–	–	✓	Jordan	House-hold	✓	✓	–	–
Aliyu & Tekbiyik-Ersoy (2019) [65]		LP	Cost	–	✓/-	✓	✓	–	–	–	–	–	Nigeria	Village	✓	✓	✓	–
Balderrama et al. (2019) [48]		MILP	Cost	✓	–	✓	✓	✓	✓	–	–	✓	Bolivia	Village	✓	✓	✓	–
Kumar et al. (2019) [135]	PSO		Cost	–	–	✓	–	✓	✓	–	–	✓	India	Village	✓	✓	✓	–
Kumar et al. (2019) [87]		MILP	Cost	✓	–	✓	–	–	–	–	✓	–	India	Village	✓	✓	✓	–
Malekpoor et al. (2019) [77]		BO-MILP	Cost, ranking of generators	–	–	✓	✓	✓	–	–	–	✓	NA	Village	✓	✓	✓	–
Lombardi et al. (2019) [54]		MILP	Cost	✓	–	✓	–	✓	–	–	–	✓	Bolivia	Village	✓	✓	✓	–
Moretti et al. (2019) [88]		MILP	Cost	–	–	✓	–	✓	–	–	–	✓	Sub-Saharan Africa	Village	✓	✓	–	–
Viteri et al. (2019) [76]		ISO	Cost	✓	–	✓	✓	✓	✓	–	–	✓	Colombia	Village	✓	✓	✓	–
Zhang et al. (2019) [128]	NSGA-II		Cost, LPSP	–	–	✓	✓	–	–	–	–	–	China	Village	✓	✓	✓	–
Alshammari & Asumadu (2020) [136]	PSO, Jaya, HS		Cost	–	–	✓	✓	–	–	✓	–	–	Saudi Arabia	Village	✓	✓	✓	–
Ashtiani et al. (2020) [152]	TLBO		Cost	–	✓	✓	–	–	–	–	–	–	Iran	House-hold	✓	✓	✓	–
Bandopadhyay & Roy (2020) [147]	MFO		Cost, LPSP	–	–	✓	✓	✓	–	–	–	✓	India	Village	✓	✓	✓	–
Barakat et al. (2020)[132]	MO-PSO		Cost, LPSP, RE fraction	–	✓	✓	✓	–	–	–	–	–	Egypt	Village	✓	✓	✓	SDG13
Benalcazar et al. (2020) [49]		LP	Cost	–	–	✓	✓	✓	–	–	–	✓	Ecuador	Village	✓	✓	–	–
Bhayo et al. (2020) [138]	PSO		Cost	–	–	✓	–	–	✓	–	–	–	Malaysia	House-hold	✓	✓	–	–
Alberizzi et al. (2020) [84]		MILP	Cost	–	–	✓	✓	✓	–	–	–	✓	Italy	Village	✓	✓	–	–
Hernandez et al. (2020) [93]		MILP	NPV	–	–	–	–	–	✓	–	–	–	Peru	Village	✓	✓	–	–
Jaszczur et al. (2020) [125]	NSGA-II		Cost, CO2 emission	–	–	✓	✓	✓	–	–	–	✓	Poland	House-hold	✓	✓	✓	SDG13
Maqbool et al. (2020) [144]	Improved HS		Cost, LPSP, RE fraction, job creation	–	–	✓	–	–	–	✓	–	–	India	Village	✓	✓	✓	SDG8, SDG13
Mouachi et al. (2020) [130]	Multimodal delayed PSO		Cost, CO2 emission, LPSP	–	✓/-	✓	✓	✓	–	–	–	✓	Morocco	Village	✓	✓	✓	SDGl13
Namaganda-Kiyimba & Mutale (2020) [89]		MILP	Cost	–	–	✓	–	–	–	–	–	–	Uganda	Village	✓	✓	–	–

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While almost all of the studies propose a cost-oriented optimization framework, the optimal operational strategy problems may require the consideration of other performance measures and could also benefit from multi-objective perspectives. Kusakana [70] focuses on minimizing power drawn from the grid. Balamurugan et al. [67], Balamurugan and Kumaravel [66], Li and Qiu [126], Li et al. [127] and Rathish et al.

Table 2 (*continued*).

Article	Heuristics and metaheuristics	Model	Objective	Unc.	GC	PV	Wind	Diesel	Hydro	Biomass	Biogas	Battery	Country	Scale	SDG-7			Other
															Aff.	Sust.	Rel.	SDGs
Oviedo et al. (2020) [109]	Heuristic Approx. of gradient descent		Cost	–	–	✓	–	✓	–	–	–	✓	Colombia	Village	✓	✓	–	–
Rathish et al. (2020) [53]	GA		Cost, CO2 emission, unmet load	–	–	✓	✓	✓	–	–	–	✓	India	Village	✓	✓	✓	SGD13
Ridha et al. (2020) [133]	MO-PSO		Cost, LLP	–	–	✓	–	–	–	–	–	–	Malaysia	Village	✓	✓	✓	–
Ridha et al. (2020) [150]	MO-SSO		Cost, LLP	–	–	✓	–	–	–	–	–	–	Malaysia	Village	✓	✓	✓	–
Ridha et al. (2020) [151]	PESA-II		Cost, LLP	–	–	✓	–	✓	–	–	–	✓	Malaysia	Village	✓	✓	✓	–
Ridha et al. (2020) [148]	MADE		Cost, LLP	–	–	✓	–	–	–	–	–	–	Malaysia	Village	✓	✓	✓	–
Samy et al. (2020) [134]	MO-PSO		Cost, LPSP	–	–	–	–	✓	–	✓	–	–	Egypt	Village	✓	✓	✓	–
Stevanato et al. (2020) [55]		LP	Cost	✓	–	✓	✓	✓	–	–	–	✓	Chile	Village	✓	✓	✓	–
Suresh et al. (2020) [120]	GA		Cost	–	–	✓	✓	✓	–	✓	✓	✓	India	Multiple villages	✓	✓	–	–
Tapia et al. (2020) [113]	Messy GA		Cost, power supply	–	–	–	–	–	✓	–	–	–	Honduras	Village	✓	✓	✓	–
Yimen et al. (2020) [122]	GA		Cost	–	–	✓	✓	✓	–	–	–	✓	Nigeria	Village	✓	✓	✓	–
Zhang et al. (2020) [145]	Improved HS		Cost, LPSP	–	–	✓	✓	–	–	–	–	–	Iran	Village	✓	✓	✓	–
Fioriti et al. (2021) [141]	PSO		Cost	✓	–	✓	–	✓	–	–	–	✓	Kenya	Village	✓	✓	–	–
Ji et al. (2021) [95]		MILP	Cost	–	–	✓	–	✓	–	✓	–	✓	China	Village	✓	✓	–	–
Yu et al. (2021) [146]	SA, improved HS		Cost, LPSP	–	–	–	–	–	–	–	–	✓	Iran	Village	✓	✓	✓	–

[53] aim to establish the balance between the demand and the power supply and, Naval et al. [80] maximizes the profit obtained from the interaction between the conventional grid and the system. Regardless of the objective function, the generality of the studies that fall into the optimal power dispatch strategy category include constraints on generation and storage capacities, and power balance equations. In addition to generation limits, Nwulu and Xia [82] define additional constraints on ramp rate limits for the conventional generators.

The general structure of the optimization framework for the optimal power dispatch problems is also shaped around the problem settings such as connection to the main grid, uncertainty in the system, and the renewable technologies integrated into the system. Especially, the availability of trading schemes between the main grid and the hybrid off-grid system has a significant impact on the energy management strategy depending on the varying electricity prices. In [69,70,73,80,82,99,126,127], this interaction between the conventional grid and hybrid renewable energy systems is considered. These studies allow the electricity purchasing and selling decisions to mitigate the disadvantages arising from the use of intermittent renewable energy sources.

As demonstrated in Fig. 7, 50% of the studies on power dispatch strategy problem optimize hybrid systems with grid connection. While the remaining systems operate in the isolated mode, only 19% of them rely on battery storage to improve reliability. The solar panel is observed to be the most frequently integrated component into hybrid systems with 81%. Wind turbines are also considered in 50% of the studies. However, system parameters of hybrid renewable energy systems can be subject to uncertainty due to the intermittent nature of renewables. Nevertheless, the number of studies providing a robust design for energy management systems under uncertainty is relatively few. Balderrama et al. [48] develops a two-stage stochastic programming formulation for a hybrid system that consists of a PV array and a diesel generator as a backup source. In this formulation, the uncertainties involving the demand and solar irradiation data are taken into account. Multi-variable regression is performed to examine the changes in the solar output for different values of irradiation and temperature inputs. Stochastic log-normal noise is applied to the average of historical observations, and a realistic yearly time series is generated to consider the variations in the load profile. Similarly, Lombardi et al. [54] proposes a two-stage stochastic programming formulation for an isolated rural microgrid that includes solar panels, a diesel generator, and a battery bank. To provide a robust solution, they generate random load profiles to account for the potential scenarios with different probabilities.

The seasonality is also considered to reflect the changes in the consumption pattern and perform a more realistic analysis. Stevanato et al. [55] presents a multi-year capacity expansion formulation to optimize the size of a rural microgrid and its operational strategy. Since the capacity expansion planning is optimized for a period of 20 years, the load profile may change significantly depending on the population growth, the use of new technology appliances, and consumer behavior. Stevanato et al. [55] adopts the same load profile generation methodology provided in Lombardi et al. [54] to tackle input variability. In addition, Gbadamosi and Nwulu [68] address the stochastic characteristic of the renewables using a linear programming

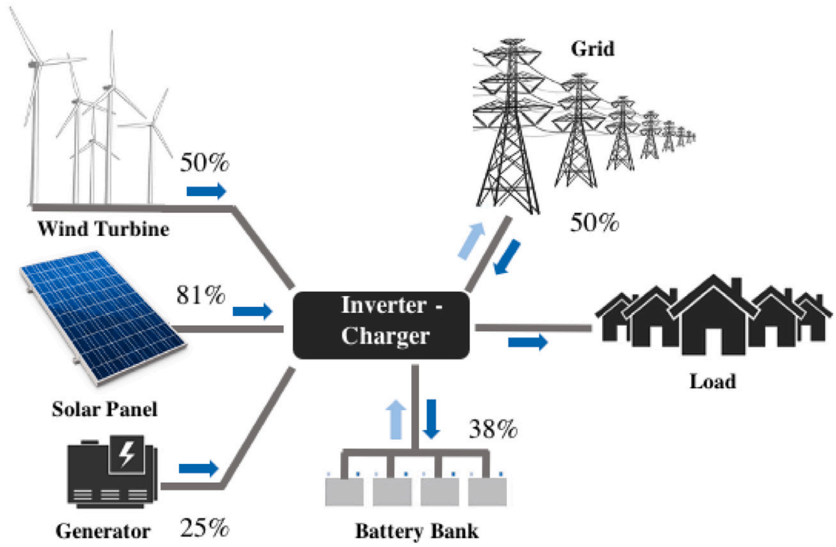

Fig. 7. Optimal power dispatch strategy problem. The numbers on the figure show the percentage of the studies including the corresponding system component.

approach to optimize the power dispatch strategy of a hybrid PV–Wind–CHP system. The system reliability analysis is performed by using a multi-state Markov model for the intermittent PV and wind-power generation.

Regarding the wide range of renewable energy sources, according to Table 3, solar generation is the most encountered renewable energy source in hybrid electrification systems. Wind power technology is the second most widely preferred renewable energy source, following the solar energy source amongst the other alternative sources such as hydroelectric systems and biomass power plants. However, the intermittent nature of the renewable sources and rural areas having no connection to the main grid leads to a high prevalence of battery banks and a diesel generators to enhance the reliability of hybrid systems, as demonstrated in Fig. 7.

The geographical distribution of the electrification projects includes 14 different countries from Europe [80], Asia [47,53,66,67,73,90,126,127], South America [48,49,54,55,69] and Africa [50–52,70,82,97–99,121]. Moreover, observing Table 3, the regional scope of these projects is generally the rural villages and only a small portion of the reviewed articles consider a household-level problem [68,73,121]. According to these observations, we can conclude that the energy management studies mostly focus on the rural villages in Asia, which is followed by the rural electrification projects in Africa, South America and Europe respectively.

Lastly, the two key attributes of SDG7, namely sustainability and affordability, are addressed in approximately 82% of the studies as indicated in Table 3. While the majority of the reviewed articles minimizes the operational costs and the electricity purchases from the main grid, the remaining studies aim to maximize the available energy or minimize the variance in the power generation [126,127], implying that reliability aspect is also taken into consideration. Moreover, Herran and Nakata [69] and Gbadamosi and Nwulu [68] use reliability constraints to maintain adequate energy supply to consumers. Unlike the previous section, optimal dispatch strategy studies are not observed to address any other SDG goal.

5. Optimal technology choice problem

Centralized and decentralized systems each have their own advantages, and the combination of these two options allows energy planners to utilize the benefit of different alternatives. Centralized systems have historically relied on fossil fuels and hydropower for electricity generation, allowing for high flexibility when dispatching electricity as well as cost sharing of generation assets amongst all grid users. On the other hand, decentralized systems can be a cost-competitive renewable energy-based option, especially for remote and hilly areas where the connection to the main grid is inconvenient and consumers consume small amounts of energy. While identifying the ideal electrification option for each consumer can be particularly challenging when the number of alternatives is large, Carvallo et al. [161] indicate that hybrid options combining on-grid systems with decentralized technologies can provide cost-effective solutions that are worthy of consideration. The main focus of the studies in this section is to compare off-grid and on-grid electrification alternatives for each demand point, identify grid-compatible nodes for which the on-grid electrification is cost-efficient, and build a power distribution network between these points. Especially for off-grid systems, the studies tend to feature the different associated generation technologies. In this section, we examine 16 articles. Table 4 summarizes them based on the optimization approach, objective, location, scale, resolution of the case studies, and the sustainable development goals addressed in the reviewed articles.

The traditional optimization techniques such as LP and MILP are useful for representing decision choice problems between centralized and off-grid systems. There is a higher share of MILP approaches due to its ability to model binary choices between whether or not to include different technology options. Nagai et al. [71] proposes a linear programming model to obtain the optimal combination of centralized and decentralized systems. Similarly, Bolukbasi and Kocaman [83], Zeyringer et al. [79], Trotter et al. [21], Nock et al. [81] and Levin and Thomas [92] develop mixed-integer programming approaches to identify the cost-efficient electrification option for each demand node. Yamaguchi and Watabe [5] propose a theoretical perspective for the problem and present interesting analytical results. While most studies aim to provide a least-cost network, only a small portion benefits from using multi-objective optimization [21,114]. Regarding the constraints, the majority of the studies involve power flow constraints, generation, transmission, and distribution capacity constraints, and radial configuration constraints in general. Additionally, [107] imposes a distance limit on the connections between households and transformers to limit resistive losses and voltage drop.

The minimum spanning tree algorithms are widely used in electrification problems to estimate the cost of the power networks. Two well-known computational algorithms, namely Prim's algorithm [162] and Kruskal's algorithm [163] are quite useful to obtain the least-cost network which spans all demand nodes. Prim's algorithm starts with

Table 3
Optimal power dispatch strategy.

Article	Heuristics and metaheuristics	Model	Objective	Unc.	GC	PV	Wind	DG	Hydro	Biomass	Battery	Country	Scale	SDG-7			Other SDGs
														Aff.	Sust.	Rel.	
Balamurugan et al. (2009) [67]		LP	Availability of energy	–	–	✓	✓	–	–	✓	✓	India	Village	–	✓	✓	–
Herran & Nakata (2012) [69]		LP	Cost	–	✓	–	–	–	–	✓	–	Colombia	Village	✓	✓	✓	–
Balamurugan & Kumaravel (2014) [66]		LP	Availability of energy	–	–	✓	✓	–	–	✓	✓	India	Village	–	✓	✓	–
Kusakana (2015) [97]		NLP	Cost	–	–	–	–	✓	✓	–	–	South Africa	Village	✓	✓	–	–
Kusakana (2016) [98]		NLP	Cost	–	–	✓	✓	✓	✓	–	–	South Africa	Village	✓	✓	–	–
Li & Qiu (2016) [126]	NSGA-II		Variance of the power output, power generation	–	✓	✓	–	–	✓	–	–	China	Village	–	✓	✓	–
Mazzola et al. (2016) [90]		MILP	Cost	–	–	✓	–	✓	–	✓	✓	India	Village	✓	✓	–	–
Yahyaoui et al. (2016) [121]	GA		Cost	–	–	✓	✓	–	–	–	✓	Tunisia	House-hold	✓	✓	–	–
Nwulu & Xia (2017) [82]		MILP	Cost	–	✓	✓	✓	–	–	–	–	Zimbabwe	Village	✓	✓	–	–
Koko et al. (2018) [99]		NLP	Cost, Revenue from RE	–	✓	–	–	–	✓	–	–	South Africa	Village	✓	✓	–	–
Kusakana (2018) [70]		LP	Grid utilization	–	✓	✓	–	–	✓	–	–	South Africa	Village	✓	✓	–	–
Li et al. (2018) [127]	NSGA-II		Energy generation, gap between generation and consumption	–	✓	✓	–	–	✓	–	–	China	NA	✓	✓	–	–
Lee & Kum (2019) [96]		DP	Cost	–	–	✓	✓	✓	–	–	✓	NA	NA	✓	✓	–	–
Siraj et al. (2019) [73]		LP	Cost	–	✓	✓	–	–	–	–	–	India	House-hold	✓	✓	–	–
Gbadamosi & Nwulu (2020) [68]		LP	Cost	✓	–	✓	✓	–	–	–	✓	NA	House-hold	✓	✓	✓	–
Naval et al. (2020) [80]		MILP	Profit	–	✓	✓	✓	–	✓	–	–	Spain	Village	✓	✓	–	–

choosing a starting point and adds the shortest segment of this point to the network. The algorithm adds the shortest (cheapest) segment emanating from the existing points on the network until all nodes are spanned. The connections that would create cycles are avoided. On the other hand, Kruskal's algorithm sorts the segments in the non-decreasing order of their distances (costs). It starts adding the shortest (cheapest) possible segment to the network so that the resulting network does not include any cycle. Both algorithms guarantee the optimal solution when all of the nodes are connected to the network. However, since the optimal technology choice problems allow partial coverage of demand points, the original algorithms are usually used in a modified way as in [102,103,105–108], and the solutions are no longer guaranteed to be optimal. In addition to the minimum spanning tree algorithms and other greedy heuristics (e.g., in Ranaboldo et al. [110]) used in the literature, evolutionary algorithms such as NSGA-II and Strength Pareto Evolutionary Algorithm-II (SPEA2) are also used to optimize the contribution of centralized and decentralized generation [114].

As one of the earliest studies that address the trade-off between decentralized and centralized systems, Lambert and Hittle [107] proposes a solution approach at a local scale using a modified version of the Prim's minimum spanning tree algorithm and simulated annealing approach. Unlike the papers reviewed in this section, the centralized systems in [107] and [106] include a two-level network design consisting of a lower level that connects the demand points to transformers; and a high voltage network between the transformers and the source point. In other words, these papers aim to design both transmission and distribution networks, whereas the remaining studies only focus on the transmission network, except [102], which aims to build a distribution grid between demand points. The resulting grid networks have a radial configuration in all of the papers. Lambert and Hittle [107] does not consider any existing grid infrastructure, and it constructs a new distribution network from scratch instead of expanding the existing grid to uncovered demand nodes. Similarly, Levin and Thomas [92], Ranaboldo et al. [110], Bolukbasi and Kocaman [83], Corigliano et al. [102], Nock et al. [81], Karsu and Kocaman [114] and Deichmann et al. [106] approach the electrification problem with the same assumption such that there is no pre-existing grid coverage. Although most of the reviewed papers assume no pre-existing grid coverage, some studies attempt to analyze the trade-off between decentralized and centralized systems while considering the existing infrastructure [12,71,79,103,105,108,112]. Schematic illustration of the optimal technology choice problem for pre-existing and non-existent grid coverage is provided in Fig. 8.

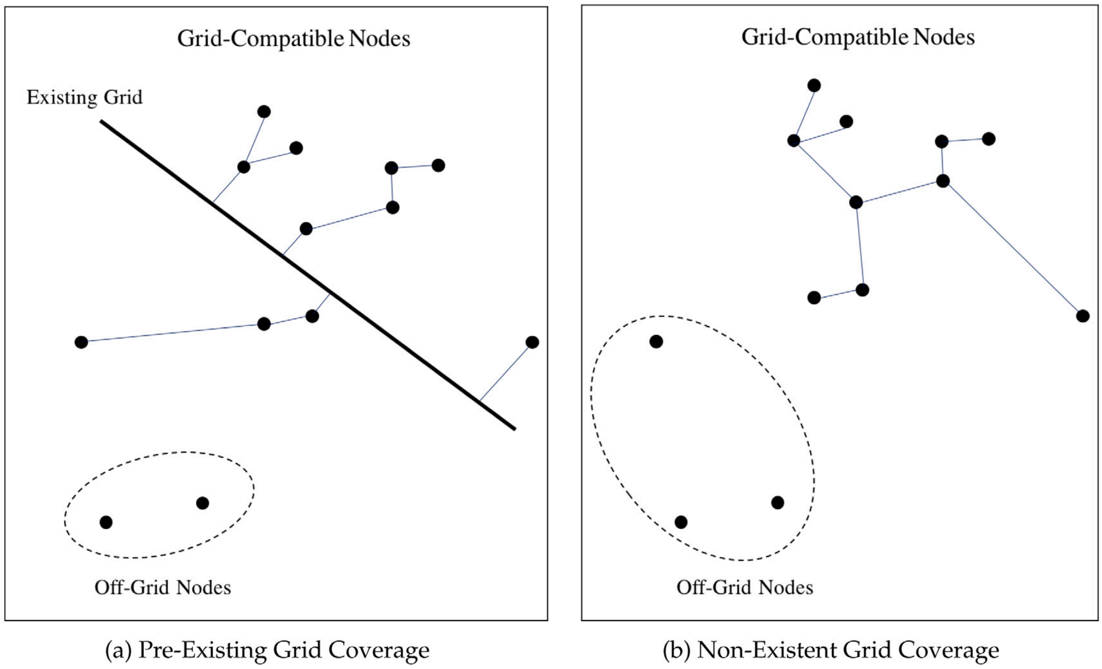

Fig. 8. Illustrations of the optimal technology choice problem under the (a) existing grid and (b) no existing grid cases.

Some researchers present an analysis through a case study and demonstrate the performance of their optimization approach on real-life instances. The geographical distribution of the regions addressed in these studies includes 13 different countries from Sub-Saharan Africa [21,79,81,92,102,103,105,106,108,112], South Asia [5,71] and South America [110]. More than half of the studies address this electrification problem in Sub-Saharan Africa, where access to electricity is the lowest in the world, as reported by World Bank. While most of the reviewed papers target the same geographical region, the scale of the electrification projects varies depending on the problem context. The majority of the studies present the results of a large-scale problem on national-level [21,71,79,81,92,103,105,108], whereas some studies provide an analysis for a smaller scale such as village-level [83,114]. When using optimization to address national scale problems researchers tend to divide the population settlements into grid cells and treat them as separate demand nodes to reduce the problem's computational complexity. The choice of the resolution is strongly dependent on the availability of the relevant data. Parshall et al. [103], Zeyringer et al. [79] and Corigliano et al. [102] use projected distances to form the discrete grid cells. On the other hand, angular resolution is used in [92,108] to provide a least-cost electrification system for Rwanda on a national scale.

All optimal technology choice studies address both affordability and sustainability aspects of SDG7 considering cost minimization and integration of renewables into the power systems. Different from the previous sections, the reliability concerns are tackled by ensuring some technical constraints such as power dynamics and voltage drop limitations in the distribution networks. In addition, SDG1 is referred to in [5] with the objective of social welfare maximization and Karsu and Kocaman [114] address SDG13 by considering concerns about the renewable penetration.

6. Optimal network design problem

Most of the extant work on rural electrification focus on the configuration of isolated hybrid renewable electrification systems, as demonstrated in Section 3. While a limited number of studies focusing on the optimal system configuration problem and the optimal technology choice problem have partially considered network design decisions in an integrated way, in this section we review 14 studies that focus on the least-cost design, planning, and operation of power distribution networks and specifically guide rural energy planners in terms of how to best design grid-based networks. These studies generally include centralized grid and mini-grid network design problems. Fig. 9 depicts single-level and multi-level network designs. In Table 5, we detail the studies in terms of proposed optimization frameworks, load-balancing and power flow requirements, case studies in underdeveloped and developing countries, the solution space, and sustainable development goals considered in these papers.

Mixed-integer programming approaches have been widely used in the power distribution network design and facility location literature because of the binary nature of the decisions, such as whether to build a generation station or a cable connection. Ferrer-Martí et al. [58], Ferrer-Martí et al. [59], Ranaboldo et al. [61], Triadó-Aymerich et al. [62], Domenech et al. [57] and Galleguillos-Pozo et al. [94] develop mixed-integer linear models to design a single microgrid system, optimize the locations of generation points and identify the cost-efficient distribution network having a radial configuration, i.e., one path between demand and generation points. On the other hand, Bonamini et al. [56] present a linear programming formulation for the optimal locations of the power plants and the consumer allocation. In this formulation, demand points are assumed to be directly connected to the generation facilities, i.e., in a topology known as star configuration. In addition to the constraints on the network design topology, power balance, capacity, and supply–demand constraints are also highlighted in these studies. Some additional constraints may also be imposed to avoid symmetries in the final configuration [58,59].

The minimum spanning tree problem is an effective tool for the network design problem type as well. In parallel with this, Zvoleff et al. [101], Kocaman et al. [43], Shrestha et al. [104] and Fobi et al. [100] propose novel solution approaches based on well-known minimum spanning tree algorithms such as Prim's Algorithm and Kruskal's Algorithm mentioned in Section 5. In addition to these practical methods, evolutionary algorithms are also preferred in network design studies. Using the shortest path algorithm and genetic algorithm respectively, Vai et al. [63] obtain a minimum cost radial topology and optimal sizing of the equipment for a rural village in Cambodia.

Table 4
Optimal technology choice: decentralized vs. centralized systems.

Article	Heuristics and metaheuristics	Model	Objective	Country	Scale	Resolution	Existing grid	SDG-7			Other SDGs
								Aff.	Sust.	Rel.	
Lambert Hittle (2000) [107]	Modified Prim's algorithm, SA		Cost	N/A	Village	Household	–	✓	✓	–	–
Yamaguchi & Watabe (2007)[5]		Theo-retical	Social welfare	Myanmar	National	Community	–	✓	✓	–	SDG1
Parshall et al. (2009) [103]	Kruskal's algorithm		Cost	Kenya	National	Grid cells (15 km^2)	✓	✓	✓	✓	–
Nagai et al. (2010) [71]		LP	Cost	Papua New Guinea	National	County	✓	✓	✓	–	–
Deichmann et al. (2011) [106]	Modified Prim's algorithm		Cost	Ethiopia, Ghana, Kenya	National	Village	–	✓	✓	–	–
Levin & Thomas (2012) [108]	Weighted composite Prim's algorithm		Cost	Botswana, Uganda, Bangladesh	National	Grid cells (770 km^2)	✓	✓	✓	–	–
Sanoh et al. (2012) [105]	Modified Kruskal's algorithm		Cost	Senegal	National	Village	✓	✓	✓	–	–
Levin & Thomas (2013) [92]		MILP	Cost	Rwanda	National	Grid cells (2.5 arcminutes)	–	✓	✓	✓	–
Ranaboldo et al. (2013) [110]	Greedy heuristic		Cost	Peru	Village	Household	–	✓	✓	-	
Zeyringer et al. (2015) [79]		MILP	Cost	Kenya	National	Grid cells (2000 km^2)	✓	✓	✓	-	
Abdul-Salam & Phimister (2016) [112]	Hierarchical lexicographic optimization		Cost	Ghana	National	Village	✓	✓	✓	–	–
Bolukbasi & Kocaman (2018) [83]		MILP	Cost	N/A	Multiple villages	Village	–	✓	✓	-	
Trotter et al. (2019) [21]		MO-MILP	Cost, Energy equity	Uganda	National	District	✓	✓	✓	–	SDG10
Corigliano et al. (2020) [102]	Kruskal's algorithm, Dijkstra algorithm		Cost	Mozam-bique	Village	Grid cells (0.04 km^2)	–	✓	✓	–	–
Nock et al. (2020) [81]		MILP	Overall stakeholder utility	Liberia	National	County	–	✓	✓	–	–
Karsu & Kocaman (2021) [114]	SPEA2, NSGA-II	BO-MILP	Cost, CO2 emission	N/A	Multiple villages	Village	–	✓	✓	–	SDG13

Some studies consider voltage drop limitations to design the optimal distribution network for final consumers. In these studies, the voltage drop across the branches of the radial distribution is forced to take a value in between the minimum and maximum voltage drop limits. To calculate the voltage drop, one needs to observe the power flow between the demand points in the network. Therefore, Ferrer-Martí et al. [58], Ferrer-Martí et al. [59], Ranaboldo et al. [61], Ranaboldo et al. [60], Triadó-Aymerich et al. [62] and Domenech et al. [57] define some decision variables related to the flow of the power in the network to keep the voltage drop at the desired level. These decision variables also determine the connections between nodes, and thus the final network is established considering the power flow between any two points in the area. Although they increase the accuracy of the proposed networks, technical constraints limit the problem's size and require the planners to focus on smaller areas. On the other hand, some other studies aim to assist planners in making rapid assessments about the cost of the electrification projects [43,63,100,101,104]. These studies ignore or "relax" some technical constraints and propose heuristic approaches to develop a guide for planning with large-scale datasets rather than a tool that provides every detail.

Most studies focus on a site-selecting problem working on a discrete solution space with a set of pre-determined candidate facility locations to determine the optimal locations for the generation points or the transformers. Kocaman et al. [43] and Fobi et al. [100], however, present site-generating optimization frameworks to determine a two-level network and the transformer locations on the euclidean space. These studies adopt an agglomerative hierarchical clustering approach to determine the clusters of households electrified by the same transformer and locate the transformers at the centroid of each cluster. Once all of the transformers are located, they construct a radial distribution network, including the demand points assigned to that particular transformer. For this purpose, both of the studies implement Essau-William's heuristic algorithm [165] to build a multi-point low voltage network having a radial configuration.

The computational frameworks shown in Table 5 are mostly applied to the non-electrified villages in Sub-Saharan Africa [43,61,101], South America [58–60,62] and South Asia [40,63,104]. On the other hand, [100] proposes a scalable approach to provide results in the administrative and sub-administrative levels for 9.2 million structures in Kenya.

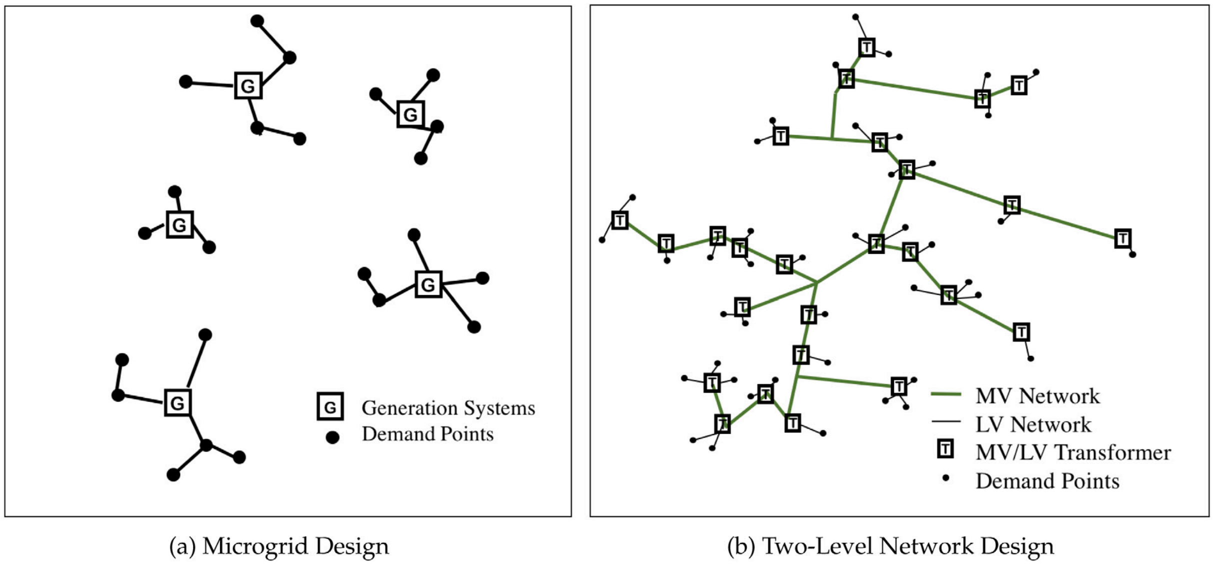

Fig. 9. Illustrations of the optimal design problem for (a) single-level and (b) multi-level networks.

In conclusion, the majority of network design studies are observed to consider affordability and sustainability aspects of SDG7. Reliability concerns are also addressed in approximately 50% of the reviewed articles in this problem type. Similar to the optimal technology choice problems, the security of the supply quality is ensured by the consideration of voltage drop and power loss constraints as in [58–61]. Apart from SDG7, none of the other sustainable development goals are referred in the network design problems.

7. Conclusion and future directions

Below, we provide a list of possible directions for the rural electrification studies with an optimization perspective and conclude our paper:

7.1. Discussion and future perspectives

While the rural electrification literature using optimization approaches has been quickly expanding, our review has exposed four types of essential research gaps in the literature, relating to the extant literature's issues with (1) planning to meet energy access-related SDGs, (2) adequately integrating on-grid and off-grid options, (3) utilizing accurate and high-resolution technical, supply and demand data to expand its scope, and (4) expanding to include additional methodological complexity to be closer to real-world circumstances:

(1) Limited ability to fully address energy-enabled SDGs:

- SDG7 possesses a range of salient synergies and trade-offs to a large number of other SDGs, implying the merits of explicitly considering multiple objectives in electrification planning [20]. The generalized rural electrification tools, however, may not be flexible enough to capture this multi-objective nature of rural electrification. As mentioned in Ciller and Lumbreras [14], there are no rural electrification tools that consider multiple objectives and existing tools only consider an economic objective. However, other criteria such as reliability, equity, various environmental impacts, food security and gender equality may create trade-offs with financial objectives. We identified a minority of 23 papers in this review that consider conflicting objectives and propose a multi-objective framework, with the type of objective functions covering only a fraction of the existing links to other SDGs as discussed by Nerini et al. [20], and more recently Bisaga et al. [8]. Therefore, there is a clear need for multi-objective optimization applications in rural electrification and this need would require more customized approaches rather than existing tools developed for general purposes.
- Optimization approaches are well-suited to simultaneously consider the three different aspects of achieving SDG7, namely affordability, reliability and sustainability. Indeed, we find a considerable number of optimization studies which integrate all three of aspects in a conjunct fashion. Depending on context, there can be significant trade-offs between choosing the least-cost technology, ensuring sufficient reliability in terms of avoiding both power outages and voltage drops and choosing sustainable, low-carbon technologies. Thus, there is potential to combine integrated optimization approaches with other rural electrification planning approaches such as GIS-based analysis with high spatial resolution to better inform policy makers how to foster high-quality and sustainable access to affordable electricity, and what the associated trade-offs are.

(2) Limited coverage of integrated on-grid and off-grid approaches:

- In 2015, World Bank developed a multi-tier framework to track the progress in universal access to electricity with a standardized approach while accounting for various key attributes such as the quality, reliability, and affordability of energy supply [166]. This framework has enabled energy planners to capture multiple dimensions of energy supply and measure the energy access using a standard tool. Please note that according to this tool, having an electricity connection does not necessarily mean having access to electricity; dimensions such as reliability and affordability should be also considered in the definition of electricity access. Considering these various dimensions, World Bank has defined six tiers for this new measurement methodology, where Tier-0 and Tier-5 denote the poorest and highest levels of electricity access, respectively. In some studies, this multi-tier metric is observed to significantly impact the choice of an appropriate method and technology to be used in the electrification of developing countries. For instance, Mentis et al. [15] demonstrated that although off-grid solutions could be an attractive option for the lower access levels such as Tier-1 or Tier-2, mini-grid or grid-connected systems become essential as the energy access target increases. Similarly, Levin and Thomas [167] argued that on-grid energy systems are still crucial to enhance the living standards of the

Table 5
Network design problem.

Article	Heuristics and metaheuristics	Model	Objective	Power flow	Country	Scale	Resolution	Solution space	SDG-7			Other SDGs
									Aff.	Sust.	Rel.	
Zvoleff et al. (2009)[101]	Composite Prim's algorithm		Cost	–	Tanzania, Senegal, Uganda, Mali	Village	Household	Discrete	✓	–	–	–
Ferrer-Marti et al. (2011) [58]		MILP	Cost	✓	Peru	Village	Household	Discrete	✓	✓	✓	–
Kocaman et al. (2012) [43]	Agglomerative clustering, Essau Williams's heuristic, Prim's algorithm		Cost	–	Sub-Saharan Africa	Village	Household	Continuous	✓	–	–	–
Ferrer-Marti et al. (2013) [59]		MILP	Cost	✓	Peru	Village	Household	Discrete	✓	✓	✓	–
Ranaboldo et al. (2014) [61]		MILP	Cost	✓	Cape Verde	Village	Household	Discrete	✓	✓	✓	–
Ranaboldo et al. (2014) [60]	Greedy heuristic		Cost	✓	Peru	Village	Household	Discrete	✓	✓	✓	–
Bazmi et al. (2015) [40]		MINLP	Cost	–	Malaysia	State (Johor)	Market center	Discrete	✓	✓	–	–
Triado-Aymerich et al. (2016) [62]	Relax and fix, corridor method increasing radius		Cost	✓	Peru	Village	Household	Discrete	✓	✓	✓	–
Shrestha et al. (2016) [104]	Kruskal's algorithm		Cost	–	Nepal	Village	Household	Discrete	✓	✓	–	–
Domenech et al. (2018) [57]		MILP	Cost	✓	Spain	Village	Household	Discrete	✓	✓	✓	–
Bonamini et al. (2019) [56]		LP	Cost	–	India	Village	Household	Discrete	✓	✓	–	–
Vai et al. (2020) [63]	Shortest path algorithm, GA		Cost	✓	Cambodia	Village	Household	Discrete	✓	✓	✓	–
Fobi et al. (2021) [100]	Agglomerative clustering, Essau Williams's heuristic, Prim's algorithm		Cost	–	Kenya	National	Household	Continuous	✓	–	–	–
Galleguillos-Pozo et al. (2021) [94]		Fuzzy MILP	Cost	✓	Peru	Village	Household	Discrete	✓	✓	–	–

unelectrified population through Tier-4 and Tier-5 access levels. This review has shown that off-grid stand-alone systems have been extensively studied in the literature, whereas centralized energy systems are observed to be understudied. Thus, this review highlights the need for more studies on networked electrification options and centralized systems to improve end-user experiences by providing reliable and affordable electricity.

(3) Limited usage of high-resolution technical, supply and demand data:

- The availability of relevant data for the developing countries with low electrification rates seems to be one of the significant obstacles for researchers to direct their attention to these problematic areas. The unequal distribution of the rural electrification studies can be improved by drawing the attention of the researchers to the lack of relevant studies for the areas having inadequate electrification rates. A number of countries with very low electricity access rates have still not been covered in the literature, jeopardizing the goal to provide universal access to modern forms of energy to all by 2030. Moreover, we need greater collaborations between academic institutions in the Global North and Global South, as well as with governments to better inform planning. Governments should be encouraged to assist researchers in finding related data and building academic collaborations to develop an effective electrification strategy for the future.
- The majority of the studies on choosing the best electrification option among grid, mini-grid, and off-grid options use village or county-level data. However, the question can still be valid within a village using a high-resolution dataset that involves the geospatial locations of the final consumers such as dwellings, schools, clinics, etc. Identifying households that are too far from neighboring structures to cost-effectively serve with the grid and instead are appropriate for off-grid alternatives such as solar home systems is a challenging task that needs more attention given various distribution patterns of demand settlements. For example, preliminary analyzes of geospatial household settlement patterns in rural Ethiopia suggest high inter-household distances, leading to high "last mile" costs of low voltage lines and connections. The scarcity of the analyzes, primarily due to limited data,

on the final consumer level might be a contributing factor to low access rates [168].
- As mentioned in [81], demand can be problematic to estimate, especially in areas that historically have not had electricity access. The reasons for that might be the uncertainty regarding the electricity consumption behavior, ability to consistently afford electricity services, and willingness or ability to adopt electricity appliances. Yet, estimating both residential and business demand is quite essential, especially for the optimal system configuration and unit sizing problem. Therefore, in addition to the optimization methods, forecasting tools can also play important roles to estimate demand with more accuracy.

(4) Lack of complexity in mathematical optimization models for rural electrification:

- This review has shown that the mathematical models developed for rural electrification problems are mainly linear and mixed-integer linear programming models. However, these models may require some linearization assumptions, which may not adequately reflect the complex nature of the systems. While some problems can be more realistically modeled using dynamic programming or non-linear programming techniques, which may not need such assumptions, only a few studies in rural electrification literature utilize these methods. In addition, metaheuristic approaches, especially GA and PSO, are among the most frequently used optimization techniques in rural electrification studies. Compared to the mathematical models, these methods can be more flexible, capturing the complexity inherent in the problems, yet they still need to fit the problem into an algorithmic framework. On the other hand, heuristic approaches are more customized methodologies, which might be quite useful considering the site-specific requirements of rural electrification studies.
- While metaheuristic and heuristic approaches might be practical methods that can provide "acceptable" solutions in an "acceptable" amount of time, they may not guarantee the solution quality. Another category of optimization methods would be approximation algorithms. However, no approximation algorithm is proposed for the rural electrification problems that can efficiently solve the problem with a guarantee on the solution quality. Therefore, this review reveals the need for acknowledging the trade-off between solution time and solution quality in optimization methods used in the literature.
- Rural electrification problems generally deal with greenfield areas that have no existing infrastructure. Since there is no restricting infrastructure in these areas, new facilities can be located at almost any point in continuous space, motivating site-generating facility location–allocation studies as opposed to site-selecting ones [169]. This review identified only two studies in the network design problems that propose a solution approach using continuous space rather than pre-determined discrete candidate locations for the facilities. Greenfield development studies can benefit from continuous optimization problems more.
- Renewable energy sources, as well as energy demand, can be highly uncertain. Optimization models that take this uncertainty into account in the planning and management of the systems can lead to remarkable savings. Therefore, rural electrification studies can significantly benefit from stochastic and robust optimization techniques.

Putting these literature gaps into a broader perspective, three main types of barriers and challenges emerge with respect to using optimization approaches for rural electrification, namely (1) methodological issues, (2) data-related issues, (3) implementation and scaling issues. First, as discussed above, the key methodological challenge is the limitation of optimization methods in high-resolution problems. Due to their computational complexity, their accuracy in real-life settings can be limited where too generic assumptions have to be used to enable finding an optimal solution. A key methodological consequence is the tendency of the deployed models to be comparably inflexible. For instance, the overwhelming majority of models reviewed in this paper are designed to be deterministic rather than accounting for the stochastic nature of demand, weather patterns, energy prices, and other factors. Furthermore, our review did not identify a single paper that combined more than two of the four proposed sub-problems of rural electrification. It is conceivable, however, to combine the optimal system configuration and unit sizing problem with both the optimal power dispatch problem and the optimal network design problem.

Second, as discussed above, the quality of optimization model output tends to depend on its input data. Scarcity of high-quality input data can be a critical problem for rural areas in low-income countries which may limit the insights optimization models can have for decision makers. It is key to note, however, that there have been recent significant advances in terms of the quality of satellite imagery used for rural development projects both from academia as well as the private sector which use big data analytics approaches to bridge existing data gaps [170].

Third, and critically, there remains a key gap between academic model results and practitioner decisions, with optimization models being a comparably new approach to rural electrification planning in some low-income country contexts. To ensure that academic work has an impact on the ground, it is key to engage with local stakeholders to obtain their input and tailor modeling approaches to the realities on the ground, as well as building sufficient local energy planning skills amongst national-level decision makers to ensure that modeling insights feed into and improve existing rural electrification policy strategies.

7.2. Overall conclusions

In this paper, we review the current state of the art in optimization methods developed and applied to the rural electrification problem. We identify 111 scientific articles which propose either new a mathematical model, a heuristic, or a metaheuristic approach for solving different aspects of rural electrification challenges. We note that more than 70% of studies reviewed have been published in the last five years. We proposed four different archetypes of problems related to rural electrification based on the type of problem they solve, namely (i) optimal system configuration and unit sizing, (ii) optimal power dispatch strategy, (iii) optimal technology choice, and (iv) optimal network design. With this review paper, we provide a list of optimization methods (see Table 1) that researchers in the rural electrification field can use and aim to draw the attention of the operations research scientists to the unique problems that need urgent attention to achieve SDG7, and other SDGs linked to SDG7.

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.

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References

[1] UNDP. Goal7: Affordable and clean energy. 2015, https://www.undp.org/content/undp/en/home/sustainable-development-goals/goal-7-affordable-and-clean-energy/targets.html, (Accessed 2019-12-13).

[2] World Bank. Access to electricity. 2018, https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS?view=map (Accessed 2021-05-03).

[3] Trotter Philipp A. Rural electrification, electrification inequality and democratic institutions in sub-saharan africa. Energy Sustain Dev 2016;34:111–29.

[4] Cook Paul. Infrastructure, rural electrification and development. Energy Sustain Dev 2011;15(3):304–13.

[5] Yamaguchi Kaoru, Watabe Akihiro. Rural electrification in developing countries: Conflicts between local technological innovation and the national electrification policy. J Energy Dev 2007;33(1):105–28.

[6] Trotter Philipp A, Abdullah Sabah. Re-focusing foreign involvement in sub-saharan africa's power sector on sustainable development. Energy Sustain Dev 2018;44:139–46.

[7] Alova Galina, Trotter Philipp A, Money Alex. A machine-learning approach to predicting africa's electricity mix based on planned power plants and their chances of success. Nat Energy 2021;6(2):158–66.

[8] Bisaga Iwona, Parikh Priti, Tomei Julia, To Long Seng. Mapping synergies and trade-offs between energy and the sustainable development goals: A case study of off-grid solar energy in rwanda. Energy Policy 2021;149:112028.

[9] IEA. SDG7: Data and projections. 2021, https://www.iea.org/reports/sdg7-data-and-projections/access-to-electricity (Accessed 2019-12-22).

[10] Batidzirai Bothwell, Trotter Philipp A, Brophy Aoife, Stritzke Susann, Moyo Alfred, Twesigye Peter, Puranasamriddhi Akaraseth, Madhlopa Amos. Towards people-private-public partnerships: An integrated community engagement model for capturing energy access needs. Energy Res Soc Sci 2021;74:101975.

[11] Baker Erin, Nock Destenie, Levin Todd, Atarah Samuel A, Afful-Dadzie Anthony, Dodoo-Arhin David, Ndikumana Léonce, Shittu Ekundayo, Muchapondwa Edwin, Sackey Charles Van-Hein. Who is marginalized in energy justice? Amplifying community leader perspectives of energy transitions in ghana. Energy Res Soc Sci 2021;73:101933.

[12] Trotter Philipp A, McManus Marcelle C, Maconachie Roy. Electricity planning and implementation in sub-saharan africa: A systematic review. Renew Sustain Energy Rev 2017;74:1189–209.

[13] Mandelli Stefano, Barbieri Jacopo, Mereu Riccardo, Colombo Emanuela. Off-grid systems for rural electrification in developing countries: Definitions, classification and a comprehensive literature review. Renew Sustain Energy Rev 2016;58:1621–46.

[14] Ciller Pedro, Lumbreras Sara. Electricity for all: The contribution of large-scale planning tools to the energy-access problem. Renew Sustain Energy Rev 2020;120:109624.

[15] Mentis Dimitrios, Howells Mark, Rogner Holger, Korkovelos Alexandros, Arderne Christopher, Zepeda Eduardo, Siyal Shahid, Taliotis Costantinos, Bazilian Morgan, de Roo Ad, et al. Lighting the world: the first application of an open source, spatial electrification tool (onsset) on sub-saharan africa. Environ Res Lett 2017;12(8):085003.

[16] Bissiri Mounirah, Moura Pedro, Figueiredo Nuno Carvalho, da Silva Patrícia Pereira. A geospatial approach towards defining cost-optimal electrification pathways in west africa. Energy 2020;200:117471.

[17] Korkovelos Alexandros, Khavari Babak, Sahlberg Andreas, Howells Mark, Arderne Christopher. The role of open access data in geospatial electrification planning and the achievement of sdg7. an onsset-based case study for malawi. Energies 2019;12(7).

[18] Mentis Dimitrios, Welsch Manuel, Nerini Francesco Fuso, Broad Oliver, Howells Mark, Bazilian Morgan, Rogner Holger. A gis-based approach for electrification planning—A case study on nigeria. Energy Sustain Dev 2015;29:142–50.

[19] Taye Biniyam Zemene, Workineh Tewodros Gera, Nebey Abraham Hizikiel, Kefale Habtemariam Aberie. Rural electrification planning using geographic information system (gis). Cogent Eng 2020;7(1):1836730.

[20] Nerini Francesco Fuso, Tomei Julia, To Long Seng, Bisaga Iwona, Parikh Priti, Black Mairi, Borrion Aiduan, Spataru Catalina, Broto Vanesa Castán, Anandarajah Gabrial, et al. Mapping synergies and trade-offs between energy and the sustainable development goals. Nat Energy 2018;3(1):10–5.

[21] Trotter Philipp A, Cooper Nathanial J, Wilson Peter R. A multi-criteria, long-term energy planning optimisation model with integrated on-grid and off-grid electrification–the case of uganda. Appl Energy 2019;243:288–312.

[22] Ciller Pedro, de Cuadra Fernando, Lumbreras Sara. Optimizing off-grid generation in large-scale electrification-planning problems: A direct-search approach. Energies 2019;12(24):4634.

[23] Malik Prashant, Awasthi Mamta, Sinha Sunanda. Biomass-based gaseous fuel for hybrid renewable energy systems: An overview and future research opportunities. Int J Energy Res 2020.

[24] Freier Daria, Ramirez-Iniguez Roberto, Jafry Tahseen, Muhammad-Sukki Firdaus, Gamio Carlos. A review of optical concentrators for portable solar photovoltaic systems for developing countries. Renew Sustain Energy Rev 2018;90:957–68.

[25] Domenech Bruno, Ferrer-Martí Laia, Pastor Rafael. Comparison of various approaches to design wind-pv rural electrification projects in remote areas of developing countries. Wiley Interdiscip Rev: Energy Environ 2019;8(3):e332.

[26] Khare Vikas, Nema Savita, Baredar Prashant. Solar–wind hybrid renewable energy system: A review. Renew Sustain Energy Rev 2016;58:23–33.

[27] Ortega-Arriaga P, Babacan O, Nelson J, Gambhir A. Grid versus off-grid electricity access options: A review on the economic and environmental impacts. Renew Sustain Energy Rev 2021;143:110864.

[28] Riva Fabio, Tognollo Annalisa, Gardumi Francesco, Colombo Emanuela. Long-term energy planning and demand forecast in remote areas of developing countries: Classification of case studies and insights from a modelling perspective. Energy Strateg Rev 2018;20:71–89.

[29] Akikur Rahman K, Saidur Rahman, Ping Hew W, Ullah Khan R. Comparative study of stand-alone and hybrid solar energy systems suitable for off-grid rural electrification: A review. Renew Sustain Energy Rev 2013;27:738–52.

[30] Izadyar Nima, Ong Hwai Chyuan, Chong WT, Leong KY. Resource assessment of the renewable energy potential for a remote area: a review. Renew Sustain Energy Rev 2016;62:908–23.

[31] Liu Yanfeng, Yu Sisi, Zhu Ying, Wang Dengjia, Liu Jiaping. Modeling, planning, application and management of energy systems for isolated areas: A review. Renew Sustain Energy Rev 2018;82:460–70.

[32] Chauhan Anurag, Saini RP. A review on integrated renewable energy system based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control. Renew Sustain Energy Rev 2014;38:99–120.

[33] Tan Yingjie, Meegahapola Lasantha, Muttaqi Kashem M. A review of technical challenges in planning and operation of remote area power supply systems. Renew Sustain Energy Rev 2014;38:876–89.

[34] Mohammed YS, Mustafa MW, Bashir Naomi. Hybrid renewable energy systems for off-grid electric power: Review of substantial issues. Renew Sustain Energy Rev 2014;35:527–39.

[35] Kumar Abhishek, Sah Bikash, Singh Arvind R, Deng Yan, He Xiangning, Kumar Praveen, Bansal RC. A review of multi criteria decision making (mcdm) towards sustainable renewable energy development. Renew Sustain Energy Rev 2017;69:596–609.

[36] Rojas-Zerpa Juan C, Yusta Jose M. Application of multicriteria decision methods for electric supply planning in rural and remote areas. Renew Sustain Energy Rev 2015;52:557–71.

[37] Ridha Hussein Mohammed, Gomes Chandima, Hizam Hashim, Ahmadipour Masoud, Heidari Ali Asghar, Chen Huiling. Multi-objective optimization and multi-criteria decision-making methods for optimal design of standalone photovoltaic system: A comprehensive review. Renew Sustain Energy Rev 2021;135:110202.

[38] Erdinc Ozan, Uzunoglu Mehmet. Optimum design of hybrid renewable energy systems: Overview of different approaches. Renew Sustain Energy Rev 2012;16(3):1412–25.

[39] Siddaiah Rajanna, Saini RP. A review on planning, configurations, modeling and optimization techniques of hybrid renewable energy systems for off grid applications. Renew Sustain Energy Rev 2016;58:376–96.

[40] Bazmi Aqeel Ahmed, Zahedi Gholamreza. Sustainable energy systems: Role of optimization modeling techniques in power generation and supply—A review. Renew Sustain Energy Rev 2011;15(8):3480–500.

[41] Bahramara S, Moghaddam M Parsa, Haghifam MR. Optimal planning of hybrid renewable energy systems using homer: A review. Renew Sustain Energy Rev 2016;62:609–20.

[42] Jacome Veronica, Klugman Noah, Wolfram Catherine, Grunfeld Belinda, Callaway Duncan, Ray Isha. Power quality and modern energy for all. Proc Natl Acad Sci 2019;116(33):16308–13.

[43] Kocaman Ayse Selin, Huh Woonghee Tim, Modi Vijay. Initial layout of power distribution systems for rural electrification: A heuristic algorithm for multilevel network design. Appl Energy 2012;96:302–15.

[44] Gokbayrak Kagan, Kocaman Ayse Selin. A distance-limited continuous location-allocation problem for spatial planning of decentralized systems. Comput Oper Res 2017;88:15–29.

[45] León Javier, Martín-Campo F Javier, Ortuño M Teresa, Vitoriano Begoña, Carrasco Luis Miguel, Narvarte Luis. A methodology for designing electrification programs for remote areas. CEJOR Cent Eur J Oper Res 2020;28(4):1265–90.

[46] Carrasco LM, Martín-Campo FJ, Narvarte L, Ortuño M Teresa, Vitoriano Begoña. Design of maintenance structures for rural electrification with solar home systems. The case of the moroccan program. Energy 2016;117:47–57.

[47] Bala BK, Siddique Saiful Azam. Optimal design of a pv-diesel hybrid system for electrification of an isolated island—sandwip in bangladesh using genetic algorithm. Energy Sustain Dev 2009;13(3):137–42.

[48] Balderrama Sergio, Lombardi Francesco, Riva Fabio, Canedo Walter, Colombo Emanuela, Quoilin Sylvain. A two-stage linear programming optimization framework for isolated hybrid microgrids in a rural context: The case study of the "el espino" community. Energy 2019;188:116073.

[49] Benalcazar Pablo, Suski Adam, Kamiński Jacek. Optimal sizing and scheduling of hybrid energy systems: The cases of morona santiago and the galapagos islands. Energies 2020;13(15):3933.

[50] Dufo-López Rodolfo, Cristóbal-Monreal Iván R, Yusta José M. Optimisation of pv-wind-diesel-battery stand-alone systems to minimise cost and maximise human development index and job creation. Renew Energy 2016;94:280–93.
[51] Cristóbal-Monreal Iván R, Dufo-López Rodolfo. Optimisation of photovoltaic–diesel–battery stand-alone systems minimising system weight. Energy Convers Manage 2016;119:279–88.
[52] Sigarchian Sara Ghaem, Orosz Matthew S, Hemond Harry F, Malmquist Anders. Optimum design of a hybrid pv–csp–lpg microgrid with particle swarm optimization technique. Appl Therm Eng 2016;109:1031–6.
[53] Rathish Rajendran Joseph, Mahadevan Krishnan, Selvaraj Senthil Kumaran, Booma Jayapalan. Multi-objective evolutionary optimization with genetic algorithm for the design of off-grid pv-wind-battery-diesel system. Soft Comput 2020;1–20.
[54] Lombardi Francesco, Colmbo Emanuela, Balderrama Sergio, Quoilin Sylvain, et al. Two-stage stochastic sizing of a rural micro-grid based on stochastic load generation. In: 2019 ieee milan powertech. IEEE; 2019, p. 1–6.
[55] Stevanato Nicolò, Lombardi Francesco, Guidicini Giulia, Rinaldi Lorenzo, Balderrama Sergio L, Pavičević Matija, Quoilin Sylvain, Colombo Emanuela. Long-term sizing of rural microgrids: Accounting for load evolution through multi-step investment plan and stochastic optimization. Energy Sustain Dev 2020;58:16–29.
[56] Bonamini Giorgio, Colombo Emanuela, Llorca Natividad, Sanchez-Soriano Joaquin. Cost allocation for rural electrification using game theory: A case of distributed generation in rural India. Energy Sustain Dev 2019;50:139–52.
[57] Domenech B, Ranaboldo Matteo, Ferrer-Martí Laia, Pastor R, Flynn Damian. Local and regional microgrid models to optimise the design of isolated electrification projects. Renew Energy 2018;119:795–808.
[58] Ferrer-Martí Laia, Pastor Rafael, Capó G Miquel, Velo Enrique. Optimizing microwind rural electrification projects. a case study in peru. J Global Optim 2011;50(1):127–43.
[59] Ferrer-Martí Laia, Domenech Bruno, García-Villoria Alberto, Pastor Rafael. A milp model to design hybrid wind–photovoltaic isolated rural electrification projects in developing countries. European J Oper Res 2013;226(2):293–300.
[60] Ranaboldo Matteo, García-Villoria Alberto, Ferrer-Martí Laia, Moreno Rafael Pastor. A heuristic method to design autonomous village electrification projects with renewable energies. Energy 2014;73:96–109.
[61] Ranaboldo Matteo, Lega Bruno Domenech, Ferrenbach David Vilar, Ferrer-Martí Laia, Moreno Rafael Pastor, García-Villoria Alberto. Renewable energy projects to electrify rural communities in cape verde. Appl Energy 2014;118:280–91.
[62] Triadó-Aymerich Joan, Ferrer-Martí Laia, García-Villoria Alberto, Pastor Rafael. Milp-based heuristics for the design of rural community electrification projects. Comput Oper Res 2016;71:90–9.
[63] Vai Vannak, Alvarez-Herault Marie-Cecile, Raison Bertrand, Bun Long. Optimal low-voltage distribution topology with integration of pv and storage for rural electrification in developing countries: A case study of cambodia. J Mod Power Syst Clean Energy 2020;8(3):531–9.
[64] World Bank. World development indicator. 2021, data retrieved from the World Bank Group, https://databank.worldbank.org/source/world-development-indicators.
[65] Aliyu Aliyu, Tekbiyik-Ersoy Neyre. A novel framework for cost optimization of renewable energy installations: A case study of nigeria. Energies 2019;12(22):4311.
[66] Balamurugan P, Kumaravel S. The development of a generalized optimal operating strategy for a hybrid energy system. Int J Green Energy 2014;11(4):417–30.
[67] Balamurugan P, Ashok S, Jose TL. Optimal operation of biomass/wind/pv hybrid energy system for rural areas. Int J Green Energy 2009;6(1):104–16.
[68] Gbadamosi Saheed Lekan, Nwulu Nnamdi I. Optimal power dispatch and reliability analysis of hybrid chp-pv-wind systems in farming applications. Sustainability 2020;12(19):8199.
[69] Herran Diego Silva, Nakata Toshihiko. Design of decentralized energy systems for rural electrification in developing countries considering regional disparity. Appl Energy 2012;91(1):130–45.
[70] Kusakana Kanzumba. Optimal operation scheduling of grid-connected pv with ground pumped hydro storage system for cost reduction in small farming activities. J Energy Storage 2018;16:133–8.
[71] Nagai Y, Yamamoto H, Yamaji K. Constructing low emitting power systems through grid extension in papua new guinea (png) with rural electrification. Energy 2010;35(5):2309–16.
[72] Ruiz-Alvarez S, Patino J, Márquez A, Espinosa J. Optimal design for an electrical hybrid microgrid in colombia under fuel price variation. Int J Renew Energy Res 2017;7:1535–45.
[73] Siraj Kiran, Awais Muhammad, Khan Hassan A, Zafar Ahmad, Hussain Arif, Zaffar Nauman A, Jaffery Syed Husain Imran. Optimal power dispatch in solar-assisted uninterruptible power supply systems. Int Trans Electr Energy Syst 2020;30(1):e12157.
[74] Sundaramoorthy Kumaravel. Development of the hard and soft constraints based optimisation model for unit sizing of the hybrid renewable energy system designed for microgrid applications. Int J Sustain Energy 2017;36(2):192–208.
[75] Nasir Mashood, Iqbal Saqib, Khan Hassan Abbas. Optimal planning and design of low-voltage low-power solar dc microgrids. IEEE Trans Power Syst 2017;33(3):2919–28.
[76] Viteri Juan Pablo, Henao Felipe, Cherni Judith, Dyner Isaac. Optimizing the insertion of renewable energy in the off-grid regions of colombia. J Cleaner Prod 2019;235:535–48.
[77] Malekpoor Hanif, Chalvatzis Konstantinos, Mishra Nishikant, Ramudhin Amar. A hybrid approach of vikor and bi-objective integer linear programming for electrification planning in a disaster relief camp. Ann Oper Res 2019;283(1):443–69.
[78] Kocaman Ayse Selin, Modi Vijay. Value of pumped hydro storage in a hybrid energy generation and allocation system. Appl Energy 2017;205:1202–15.
[79] Zeyringer Marianne, Pachauri Shonali, Schmid Erwin, Schmidt Johannes, Worrell Ernst, Morawetz Ulrich B. Analyzing grid extension and stand-alone photovoltaic systems for the cost-effective electrification of kenya. Energy Sustain Dev 2015;25:75–86.
[80] Naval Natalia, Sánchez Raul, Yusta Jose M. A virtual power plant optimal dispatch model with large and small-scale distributed renewable generation. Renew Energy 2020;151:57–69.
[81] Nock Destenie, Levin Todd, Baker Erin. Changing the policy paradigm: A benefit maximization approach to electricity planning in developing countries. Appl Energy 2020;264:114583.
[82] Nwulu Nnamdi I, Xia Xiaohua. Optimal dispatch for a microgrid incorporating renewables and demand response. Renew Energy 2017;101:16–28.
[83] Bolukbasi Gizem, Kocaman Ayse Selin. A prize collecting steiner tree approach to least cost evaluation of grid and off-grid electrification systems. Energy 2018;160:536–43.
[84] Alberizzi Jacopo Carlo, Frigola Joaquim Meléndez, Rossi Mosè, Renzi Massimiliano. Optimal sizing of a hybrid renewable energy system: Importance of data selection with highly variable renewable energy sources. Energy Convers Manage 2020;223:113303.
[85] Domenech B, Ferrer-Martí Laia, Pastor R. Including management and security of supply constraints for designing stand-alone electrification systems in developing countries. Renew Energy 2015;80:359–69.
[86] Kanyarusoke Kant E, Gryzagoridis Jasson, Oliver Graeme. Re-mapping sub-sahara africa for equipment selection to photo electrify energy poor homes. Appl Energy 2016;175:240–50.
[87] Kumar Arun, Sharma Sumedha, Verma Ashu. Optimal sizing and multi-energy management strategy for pv-biofuel-based off-grid systems. IET Smart Grid 2019;3(1):83–97.
[88] Moretti Luca, Astolfi Marco, Vergara Claudio, Macchi Ennio, Pérez-Arriaga Josè Ignacio, Manzolini Giampaolo. A design and dispatch optimization algorithm based on mixed integer linear programming for rural electrification. Appl Energy 2019;233:1104–21.
[89] Namaganda-Kiyimba J, Mutale J. An optimal rural community pv microgrid design using mixed integer linear programming and dbscan approach. SAIEE Afr Res J 2020;111(3):111–9. http://dx.doi.org/10.23919/SAIEE.2020.9142604.
[90] Mazzola Simone, Astolfi Marco, Macchi Ennio. The potential role of solid biomass for rural electrification: A techno economic analysis for a hybrid microgrid in india. Appl Energy 2016;169:370–83.
[91] Bazmi Aqeel Ahmed, Zahedi Gholamreza, Hashim Haslenda. Design of decentralized biopower generation and distribution system for developing countries. J Cleaner Prod 2015;86:209–20.
[92] Levin Todd, Thomas Valerie M. A mixed-integer optimization model for electricity infrastructure development. Energy Syst 2013;4(1):79–98.
[93] Hernandez Juan Carlo, Peñas Carlos Jan, Tiu Adrianne Ressa, Sy Charlle. A multi-period optimization model for the design of an off-grid micro hydro power plant with profitability and degradation considerations. Process Integr Optim Sustain 2020;1–13.
[94] Galleguillos-Pozo Rosa, Domenech B, Ferrer-Martí Laia, Pastor R. Design of stand-alone electrification systems using fuzzy mathematical programming approaches. Energy 2021;228:120639.
[95] Ji Ling, Liang Xiaolin, Xie Yulei, Huang Guohe, Wang Bing. Optimal design and sensitivity analysis of the stand-alone hybrid energy system with pv and biomass-chp for remote villages. Energy 2021;225:120323.
[96] Lee Kun, Kum Dongsuk. Complete design space exploration of isolated hybrid renewable energy system via dynamic programming. Energy Convers Manage 2019;196:920–34.
[97] Kusakana Kanzumba. Optimization of the daily operation of a hydrokinetic–diesel hybrid system with pumped hydro storage. Energy Convers Manage 2015;106:901–10.
[98] Kusakana Kanzumba. Optimal scheduling for distributed hybrid system with pumped hydro storage. Energy Convers Manage 2016;111:253–60.
[99] Koko Sandile Phillip, Kusakana Kanzumba, Vermaak Herman Jacobus. Optimal power dispatch of a grid-interactive micro-hydrokinetic-pumped hydro storage system. J Energy Storage 2018;17:63–72.
[100] Fobi Simone, Kocaman Ayse Selin, Taneja Jay, Modi Vijay. A scalable framework to measure the impact of spatial heterogeneity on electrification. Energy Sustain Dev 2021;60:67–81.

[101] Zvoleff Alex, Kocaman Ayse Selin, Huh Woonghee Tim, Modi Vijay. The impact of geography on energy infrastructure costs. Energy Policy 2009;37(10):4066–78.

[102] Corigliano Silvia, Carnovali Tommaso, Edeme Darlain, Merlo Marco. Holistic geospatial data-based procedure for electric network design and least-cost energy strategy. Energy Sustain Dev 2020;58:1–15.

[103] Parshall Lily, Pillai Dana, Mohan Shashank, Sanoh Aly, Modi Vijay. National electricity planning in settings with low pre-existing grid coverage: Development of a spatial model and case study of kenya. Energy Policy 2009;37(6):2395–410.

[104] Shrestha Ashish, Jha Shailendra Kumar, Shah Bibhu, Gautam Bidur Raj. Optimal grid network for rural electrification of upper karnali hydro project affected area. In: 2016 ieee region 10 humanitarian technology conference (r10-htc). IEEE; 2016, p. 1–5.

[105] Sanoh Aly, Parshall Lily, Sarr Ousmane Fall, Kum Susan, Modi Vijay. Local and national electricity planning in senegal: Scenarios and policies. Energy Sustain Dev 2012;16(1):13–25.

[106] Deichmann Uwe, Meisner Craig, Murray Siobhan, Wheeler David. The economics of renewable energy expansion in rural sub-saharan africa. Energy Policy 2011;39(1):215–27.

[107] Lambert Thomas William, Hittle DC. Optimization of autonomous village electrification systems by simulated annealing. Sol Energy 2000;68(1):121–32.

[108] Levin Todd, Thomas Valerie M. Least-cost network evaluation of centralized and decentralized contributions to global electrification. Energy Policy 2012;41:286–302.

[109] Oviedo JC, Suarez Johan S, Duarte C, Solano J. Sizing of hybrid islanded microgrids using a heuristic approximation of the gradient descent method for discrete functions. 2020.

[110] Ranaboldo Matteo, Ferrer-Martí Laia, García-Villoria Alberto, Moreno Rafael Pastor. Heuristic indicators for the design of community off-grid electrification systems based on multiple renewable energies. Energy 2013;50:501–12.

[111] Ranaboldo Matteo, Domenech Bruno, Reyes Gustavo Alberto, Ferrer-Martí Laia, Moreno Rafael Pastor, García-Villoria Alberto. Off-grid community electrification projects based on wind and solar energies: A case study in nicaragua. Sol Energy 2015;117:268–81.

[112] Abdul-Salam Yakubu, Phimister Euan. The politico-economics of electricity planning in developing countries: A case study of ghana. Energy Policy 2016;88:299–309.

[113] Tapia A, Reina DG, Millán P. Optimized micro-hydro power plants layout design using messy genetic algorithms. Expert Syst Appl 2020;113539.

[114] Karsu Özlem, Kocaman Ayse Selin. Towards the sustainable development goals: A bi-objective framework for electricity access. Energy 2021;216:119305.

[115] Gonzalez Arnau, Riba Jordi-Roger, Rius Antoni, Puig Rita. Optimal sizing of a hybrid grid-connected photovoltaic and wind power system. Appl Energy 2015;154:752–62.

[116] González Arnau, Riba Jordi-Roger, Rius Antoni. Optimal sizing of a hybrid grid-connected photovoltaic–wind–biomass power system. Sustainability 2015;7(9):12787–806.

[117] González Arnau, Riba Jordi-Roger, Rius Antoni. Combined heat and power design based on environmental and cost criteria. Energy 2016;116:922–32.

[118] Huang Yuansheng, Yang Lei, Liu Shijian, Wang Guangli. Cooperation between two micro-grids considering power exchange: an optimal sizing approach based on collaborative operation. Sustainability 2018;10(11):4198.

[119] Rajanna S, Saini RP. Development of optimal integrated renewable energy model with battery storage for a remote indian area. Energy 2016;111:803–17.

[120] Suresh Vendoti, Muralidhar M, Kiranmayi R. Modelling and optimization of an off-grid hybrid renewable energy system for electrification in a rural areas. Energy Rep 2020;6:594–604.

[121] Yahyaoui Imene, Yahyaoui Amani, Chaabene Maher, Tadeo Fernando. Energy management for a stand-alone photovoltaic-wind system suitable for rural electrification. Sustainable Cities Soc 2016;25:90–101.

[122] Yimen Nasser, Tchotang Theodore, Kanmogne Abraham, Abdelkhalikh Idriss Idriss, Musa Bashir, Aliyu Aliyu, Okonkwo Eric C, Abba Sani Isa, Tata Daniel, Meva'a Lucien, et al. Optimal sizing and techno-economic analysis of hybrid renewable energy systems—a case study of a photovoltaic/wind/battery/diesel system in fanisau, northern nigeria. Processes 2020;8(11):1381.

[123] Roberts Justo José, Cassula Agnelo Marotta, Silveira José Luz, da Costa Bortoni Edson, Mendiburu Andrés Z. Robust multi-objective optimization of a renewable based hybrid power system. Appl Energy 2018;223:52–68.

[124] Dufo-Lopez Rodolfo, Cristobal-Monreal Ivan R, Yusta Jose M. Stochastic-heuristic methodology for the optimisation of components and control variables of pv-wind-diesel-battery stand-alone systems. Renew Energy 2016;99:919–35.

[125] Jaszczur Marek, Hassan Qusay, Palej Patryk, Abdulateef Jasim. Multi-objective optimisation of a micro-grid hybrid power system for household application. Energy 2020;117738.

[126] Li Fang-Fang, Qiu Jun. Multi-objective optimization for integrated hydro–photovoltaic power system. Appl Energy 2016;167:377–84.

[127] Li Fang-Fang, Qiu Jun, Wei Jia-Hua. Multiobjective optimization for hydro-photovoltaic hybrid power system considering both energy generation and energy consumption. Energy Sci Eng 2018;6(5):362–70.

[128] Zhang Debao, Liu Junwei, Jiao Shifei, Tian Hao, Lou Chengzhi, Zhou Zhihua, Zhang Ji, Wang Chendong, Zuo Jian. Research on the configuration and operation effect of the hybrid solar-wind-battery power generation system based on nsga-ii. Energy 2019;189:116121.

[129] Bilal B Ould, Sambou V, Ndiaye PA, Kébé CMF, Ndongo M. Optimal design of a hybrid solar–wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP). Renew Energy 2010;35(10):2388–90.

[130] Mouachi Raja, Jallal Mohammed Ali, Gharnati Fatima, Raoufi Mustapha. Multiobjective sizing of an autonomous hybrid microgrid using a multimodal delayed PSO algorithm: A case study of a fishing village. Comput Intell Neurosci 2020;2020.

[131] Borhanazad Hanieh, Mekhilef Saad, Ganapathy Velappa Gounder, Modiri-Delshad Mostafa, Mirtaheri Ali. Optimization of micro-grid system using mopso. Renew Energy 2014;71:295–306.

[132] Barakat Shimaa, Ibrahim Haitham, Elbaset Adel A. Multi-objective optimization of grid-connected pv-wind hybrid system considering reliability, cost, and environmental aspects. Sustainable Cities Soc 2020;60:102178.

[133] Mohammed Ridha Hussein, Gomes Chandima, Hizam Hashim, Ahmadipour Masoud. Optimal design of standalone photovoltaic system based on multi-objective particle swarm optimization: A case study of malaysia. Processes 2020;8(1):41.

[134] Samy MM, Elkhouly Heba I, Barakat S. Multi-objective optimization of hybrid renewable energy system based on biomass and fuel cells. Int J Energy Res 2020.

[135] Kumar S, Kaur T, Arora MK, Upadhyay S. Resource estimation and sizing optimization of pv/micro hydro-based hybrid energy system in rural area of western himalayan himachal pradesh in india. Energy Sources A 2019;41(22):2795–807.

[136] Alshammari Nahar, Asumadu Johnson. Optimum unit sizing of hybrid renewable energy system utilizing harmony search, jaya and particle swarm optimization algorithms. Sustainable Cities Soc 2020;60:102255.

[137] Abuzeid Osama, Daoud Amjad, Barghash Mahmoud. Optimal off-grid hybrid renewable energy system for residential applications using particle swarm optimization. Jordan J Mech Ind Eng 2019;13(2).

[138] Bhayo Bilawal A, Al-Kayiem Hussain H, Gilani Syed IU, Ismail Firas B. Power management optimization of hybrid solar photovoltaic-battery integrated with pumped-hydro-storage system for standalone electricity generation. Energy Convers Manage 2020;215:112942.

[139] Homayouni Fatemeh, Roshandel Ramin, Hamidi Ali Asghar. Techno-economic and environmental analysis of an integrated standalone hybrid solar hydrogen system to supply cchp loads of a greenhouse in iran. Int J Green Energy 2017;14(3):295–309.

[140] Patel Alpeshkumar Mangaldas, Singal Sunil Kumar. Economic analysis of integrated renewable energy system for electrification of remote rural area having scattered population. Int J Renew Energy Res (IJRER) 2018;8(1):523–39.

[141] Fioriti Davide, Poli Davide, Duenas-Martinez Pablo, Perez-Arriaga Ignacio. Multi-year stochastic planning of off-grid microgrids subject to significant load growth uncertainty: overcoming single-year methodologies. Electr Power Syst Res 2021;194:107053.

[142] Chauhan Anurag, Saini RP. Size optimization and demand response of a stand-alone integrated renewable energy system. Energy 2017;124:59–73.

[143] Eteiba MB, Barakat Shimaa, Samy MM, Wahba Wael Ismael. Optimization of an off-grid pv/biomass hybrid system with different battery technologies. Sustainable Cities Soc 2018;40:713–27.

[144] Maqbool Umar, Tyagi Arjun, Tyagi VV, Kothari Richa. Optimization of the renewable-energy-based micro-grid for rural electrification in northern region of india. Clean Technol Environ Policy 2020;1–12.

[145] Zhang Ge, Shi Yong, Maleki Akbar, Rosen Marc A. Optimal location and size of a grid-independent solar/hydrogen system for rural areas using an efficient heuristic approach. Renew Energy 2020;156:1203–14.

[146] Yu Xiaomo, Li Wenjing, Maleki Akbar, Rosen Marc A, Birjandi Ali Komeili, Tang Ling. Selection of optimal location and design of a stand-alone photovoltaic scheme using a modified hybrid methodology. Sustain Energy Technol Assess 2021;45:101071.

[147] Bandopadhyay Joy, Roy Provas Kumar. Application of hybrid multi-objective moth flame optimization technique for optimal performance of hybrid micro-grid system. Appl Soft Comput 2020;95:106487.

[148] Ridha Hussein Mohammed, Gomes Chandima, Hazim Hashim, Ahmadipour Masoud. Sizing and implementing off-grid stand-alone photovoltaic/battery systems based on multi-objective optimization and techno-economic (made) analysis. Energy 2020;207:118163.

[149] Perera ATD, Attalage RA, Perera KKCK, Dassanayake VPC. Designing standalone hybrid energy systems minimizing initial investment, life cycle cost and pollutant emission. Energy 2013;54:220–30.

[150] Ridha Hussein Mohammed, Gomes Chandima, Hizam Hashim, Mirjalili Seyedali. Multiple scenarios multi-objective salp swarm optimization for sizing of standalone photovoltaic system. Renew Energy 2020;153:1330–45.

[151] Ridha Hussein Mohammed, Gomes Chandima, Hizam Hashim, Ahmadipour Masoud, Muhsen Dhiaa Halboot, Ethaib Saleem. Optimum design of a standalone solar photovoltaic system based on novel integration of iterative-pesa-ii and ahp-vikor methods. Processes 2020;8(3):367.
[152] Ashtiani Mina Najafi, Toopshekan Ashkan, Yousefi Hossein, Maleki Akbar, et al. Techno-economic analysis of a grid-connected PV/battery system using the teaching-learning-based optimization algorithm. Sol Energy 2020;203:69–82.
[153] Ghavidel Sahand, Aghaei Jamshid, Muttaqi Kashem M, Heidari Alireza. Renewable energy management in a remote area using modified gravitational search algorithm. Energy 2016;97:391–9.
[154] Babatunde OM, Munda JL, Hamam Y. A comprehensive state-of-the-art survey on hybrid renewable energy system operations and planning. IEEE Access 2020;8:75313–46. http://dx.doi.org/10.1109/ACCESS.2020.2988397.
[155] Kumar MV Manoj, Banerjee Rangan. Analysis of isolated power systems for village electrification. Energy Sustain Dev 2010;14(3):213–22.
[156] Mirjalili Seyedali. Genetic algorithm. In: Evolutionary algorithms and neural networks. Springer; 2019, p. 43–55.
[157] Cui Zhihua, Gao Xiaozhi. Theory and applications of swarm intelligence. Springer; 2012.
[158] Kennedy James, Eberhart Russell. Particle swarm optimization. In: Proceedings of icnn'95-international conference on neural networks, Vol. 4. IEEE; 1995, p. 1942–8.
[159] Kim Joong Hoon. Harmony search algorithm: A unique music-inspired algorithm. Procedia Eng 2016;154:1401–5.
[160] Hussain Kashif, Salleh Mohd Najib Mohd, Cheng Shi, Shi Yuhui, Naseem Rashid. Artificial bee colony algorithm: A component-wise analysis using diversity measurement. J King Saud Univ-Comput Inf Sci 2018.
[161] Carvallo Juan-Pablo, Taneja Jay, Callaway Duncan, Kammen Daniel M. Distributed resources shift paradigms on power system design, planning, and operation: An application of the gap model. Proc IEEE 2019;107(9):1906–22.
[162] Prim Robert Clay. Shortest connection networks and some generalizations. Bell Syst Tech J 1957;36(6):1389–401.
[163] Kruskal Joseph B. On the shortest spanning subtree of a graph and the traveling salesman problem. Proc Amer Math Soc 1956;7(1):48–50.
[164] World Bank. Access to electricity. 2018, data retrieved from SE4ALL Global Tracking Framework, https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS?view=map.
[165] Esau LR, Williams KC. A method for approximating the optimal network. IBM Syst J 1966;5(3):142–7.
[166] Bhatia Mikul, Angelou Nicolina. Capturing the multi-dimensionality of energy access. Washington, DC: World Bank; 2014.
[167] Levin Todd, Thomas Valerie M. Can developing countries leapfrog the centralized electrification paradigm? Energy Sustain Dev 2016;31:97–107.
[168] Adkins Jason Edwin, Modi Vijay, Sherpa Shaky, Han Roy, Kocaman Ayse Selin, Zhao Naichen, Natali Chris, Carbajal Jonathan. A geospatial framework for electrification planning in developing countries. In: 2017 ieee global humanitarian technology conference (ghtc). IEEE; 2017, p. 1–10.
[169] Love Robert F, Morris James G, Wesolowsky George O. Facilities location. Elsevier New York; 1988.
[170] Wu Bingfang, Tian Fuyou, Zhang Miao, Zeng Hongwei, Zeng Yuan. Cloud services with big data provide a solution for monitoring and tracking sustainable development goals. Geogr Sustain 2020;1(1):25–32.