Article

Optimal Planning of Remote Area Electricity Supply Systems: Comprehensive Review, Recent Developments and Future Scopes

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Abstract: Optimal planning of a remote area electricity supply (RAES) system is a vital challenge to achieve a reliable, clean, and cost-effective system. Various components like diesel generators, renewable energy sources, and energy storage systems are used for RAES systems. Due to the different characteristics and economic features of each component, optimal planning of RAES systems is a challengeable task. This paper presents an overview of the optimal planning procedure for RAES systems by considering the important components, parameters, methods, and data. A timely review on the state of the art is presented and the applied objective functions, design constraints, system components, and optimization algorithms are specified for the existing studies. The existing challenges for RAES systems' planning are recognized and discussed. Recent trends and developments on the planning problem are explained in detail. Eventually, this review paper gives recommendations for future research to explore the optimal planning of components in RAES systems.

Keywords: electricity cost; energy storage system; optimal planning; reliability; remote area electricity supply; renewable energy

1. Introduction

1.1. Background and Motivation

Globally, it is estimated that 17% of the world's population (about 1.2 billion people) lack access to national electricity [1]. Around 1.1 billion of these people live in Asia and Africa. The remaining 0.1 billion live in the Middle East, Latin America, and the developed countries. In Asia, 512 million people suffer from electricity inaccessibility, where 244 million live in India, 41 million in Indonesia, and 11 million in the Philippines [1]. Worldwide, deploying remote area electricity supply (RAES) systems is the main solution to provide and maintain electrification of remote areas [2]. Indeed, an RAES system is a desirable alternative for national grid extensions. Figure 1 demonstrates important sites with the necessity to develop RAES systems.

Conventionally, the RAES systems are designed based on diesel generators [3]. Reserves of fossil fuels are, however, limited and depleted rapidly, which need urgent attention and appropriate manners to eschew a potential energy crisis in the future [4]. In addition, the harmful emission of fossil fuels, including greenhouse gasses (GHGs), contributes to the global warming challenge [5]. Furthermore, the petroleum price fluctuates severely, especially after the COVID-19 pandemic. These challenges along with some other main concerns in the electricity supply for remote areas are summarized in Figure 2.

To overcome the aforementioned challenges, distributed renewable energy resources (DRERs) are competent options. DRERs use the straight environment resources to generate power that will not run out. DRERs emit little to no greenhouse gases or pollutants into the air. In most cases, DRERs require less maintenance than conventional generators,

which use traditional fuel sources. On the other side, using DRERs not only decreases the maintenance cost but also reduces the operation cost of the system. Despite all the advantages, DRERs suffer from a higher upfront cost, geographic limitations, and high intermittency [6]. Even though the prices are dropping for DRERs, energy storage systems (ESSs) are essential to overcome the intermittency problem [7]. It is worth noting that the ESS cost is not in a favorable range yet, especially when a high capacity is needed in large-scale renewable power plants. Hence, a hybrid diesel generator-DRER-ESS configuration is recommended to achieve an environmental-friendly system with a low cost. A hybrid RAES system with multiple components is, however, a complicated system and optimal planning of the system is the utmost important part. The optimal planning topic is crucial to achieve the most economical and reliable system with the lowest emission.
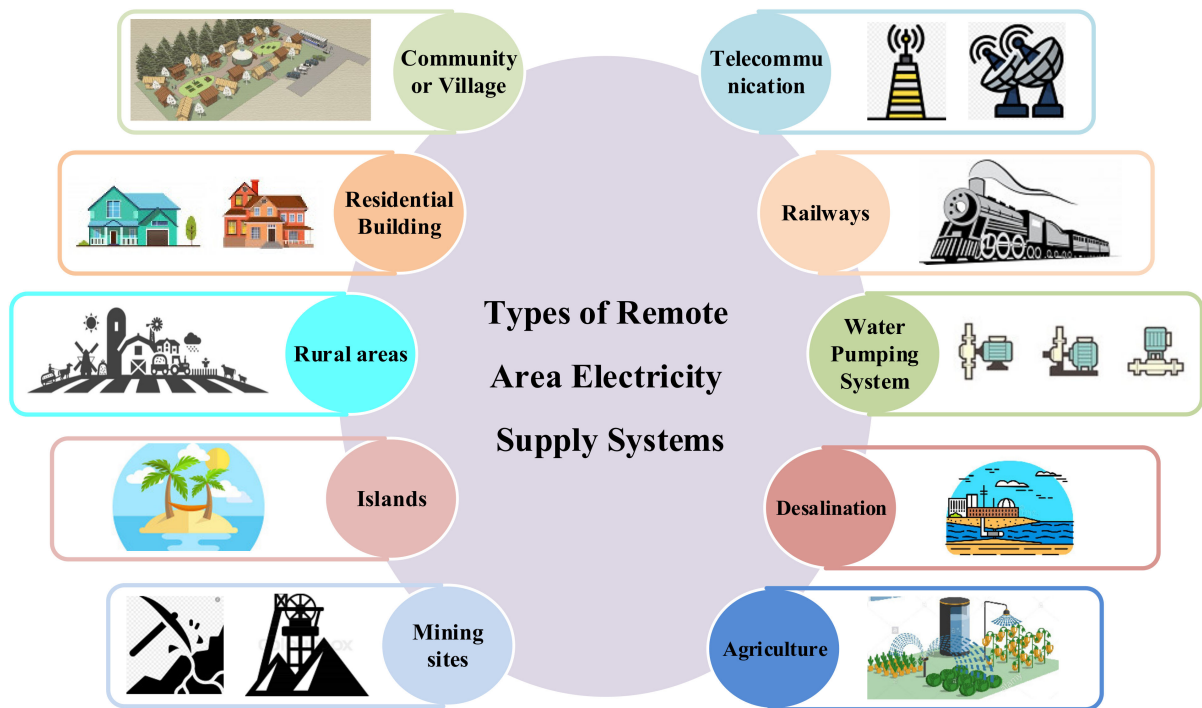

Figure 1. Important sites with the necessity to develop RAES systems.
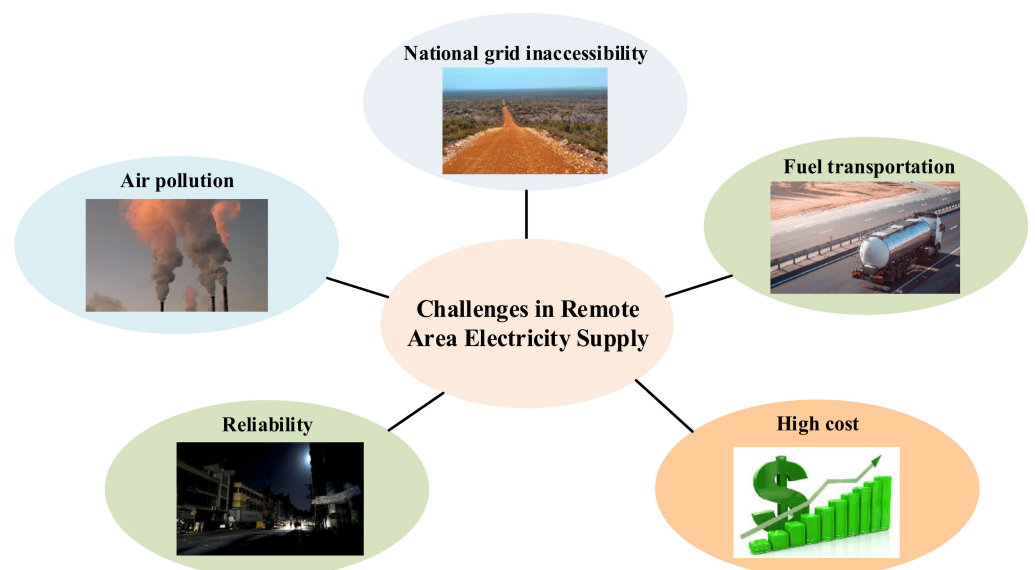

Figure 2. Electricity supply challenges in remote areas.

1.2. Critical Literature Review

A literature survey indicates several review papers on hybrid energy systems (HESs). In [8], the developments of HESs with diesel generators, solar PV, WT, and ESS were reviewed. The study investigated the types of converters and controllers without highlighting the methodology and software for solving the problem. In [9], the PV-WT hybrid renewable systems were reviewed without highlighting any technical challenges in the field. Software tools for hybrid systems based on DRERs were discussed in [10] without highlighting the methodologies. In [11], only the optimization techniques for HES were investigated without any system challenges. The energy management systems of HESs were explained in [12]. However, how the management systems can be integrated with optimal planning was not addressed. A comprehensive review on storage options and architectures for HESs was provided in [13] without highlighting their role in RAES. In [14], the HESs were investigated by addressing the model of components without addressing the sizing basics. However, these studies did not consider HESs for remote areas. The RAES systems should receive greater attention due to critical electrification issues, which were discussed in the background.

Several studies have specifically focused on standalone and remote area systems. In [15], standalone systems with solar PV, WT, and fuel cell (FC) technologies were interrogated for energy management systems. The role of the diesel generator, which is highly integrated in RAES systems, was neglected. Applications and technologies of components for RAES were analyzed in [16]. The benefits of designing a HES for off-grid systems was discussed in [17] by briefly describing the models. Different configurations of HESs for off-grid systems with description of the available components were introduced in [18]. Modelling, applications, and control of HESs for electricity supply in standalone systems were considered in [19]. The benefits of decentralized electrification of rural areas were described in [20] by discussing the electricity demand in remote communities. In [21], the development and classification of HESs for electrification in rural areas were discussed. The implementation of HESs in small communities was reviewed in [22]. However, none of those studies investigated the optimal sizing issue, which is the most important stage of RAES design.

In [23], the configuration and sizing of standalone systems were discussed without addressing any critical challenges. In [24], the optimization process and algorithms were studied. A comprehensive review of topologies, methods, and models was presented in [25]. In [26], a review was conducted on the HOMER software tool for optimal sizing. Multi-objective optimal sizing of system components in HESs was overviewed in [27]. The planning and operation of a remote area power supply was discussed in [28]. However, the study in [28] focused more on the control levels of the system without discussing the planning challenges, trends, and developments.

Based on the presented literature review, the main review gaps can be described as follows:

- The existing studies did not provide a thorough review of optimal planning of RAES systems. This includes the optimization process, input data, methods, objective functions, study based on the country, and design constraints.
- The technical challenges of the existing studies were not found by the review papers.
- The advantages and disadvantages of applied methodologies and data uncertainties for RAES optimal planning were not described by the review studies.
- The potential future directions were not introduced for researchers. Since the optimal planning problem of RAES systems is extremely critical, future perspectives should be identified to develop more significant studies.

1.3. Contribution

This paper critically reviews the optimal planning problem of energy systems for electrification of remote areas. By considering the research gaps in the literature review, this review paper contributes the following:

- Overviewing the optimization problem of RAES systems' planning.
- Conducting a review on the state of the art in optimal planning of RAES systems.
- Classifying the existing studies on optimal planning of RAES systems.
- Identifying the current technical challenges on optimal planning of RAES systems.
- Outlooking the future research trends in optimal planning of RAES systems.

A general view of the technical roadmap for this review study is illustrated in Figure 3. There are four main stages to accomplish this review study. In the first stage, problem identification is achieved by overviewing the system components, objective functions, feasibility constraints, and methodologies. In the second stage, the existing studies associated with the topic are reviewed and classified based on important factors like component, objective function, method, and country. The deficiencies in the studies are identified and explained. In the third stage, the latest developments are identified and deeply discussed. Eventually, in the fourth stage, the future trends in the optimal planning of components for remote area power supply are introduced.

Stage 1: Problem Identification

Overview on system components, objective functions, constraints, methods, ...

Stage 2: Existing Studies

Classification and review of existing studies based on important factors

Stage 3: Latest Developments

Identification and introducing recent achievements

Stage 4: Future Scopes

Introducing future perspectives based on recent shortcomings

Figure 3. A general view of the technical roadmap of this review study on optimal planning of RAES systems.

1.4. Article Organization

This paper is organized as follows. Section 2 describes the optimal planning of RAES systems with an emphasis on important factors in remote areas. The existing studies on optimal planning of RAES systems and existing challenges are scrutinized in Section 3. The latest achievements in optimal planning of RAES systems are highlighted in Section 4. The future scopes for optimal planning of RAES systems are proposed in Section 5. The conclusion is presented in Section 6.

2. Overview on Optimal Planning of RAES Systems

The optimal planning problem of RAES systems is to determine the best capacity of system components (decision variables) by minimizing/maximizing objective functions considering feasibility constraints. It is notable that in this study, it is assumed that the RAES grids are already installed, and only optimal planning of generation and storage units are investigated. This is because of the fact that the RAES grids are mostly installed and expanded by governments. Hence, there is not enough information and cost analysis

about the distribution grid installation in RAES systems. Furthermore, the generation and storage units are mostly installed close to the remote areas and hence the cost of RAES grid is highly lower than that of the conventional power systems.

A generic algorithm for optimal planning of RAES systems is demonstrated in Figure 4. The optimal planning algorithms for RAES system design are commenced with the input data of the system. Then, the system configuration of the RAES system should be specified. The optimization algorithm initializes the planning problem. The operation of the RAES system is evaluated in the next step. Satisfaction of the feasibility constraints is checked after the operation of the RAES system. If all the constraints are satisfied, the objective function is calculated to finalize the optimization problem.
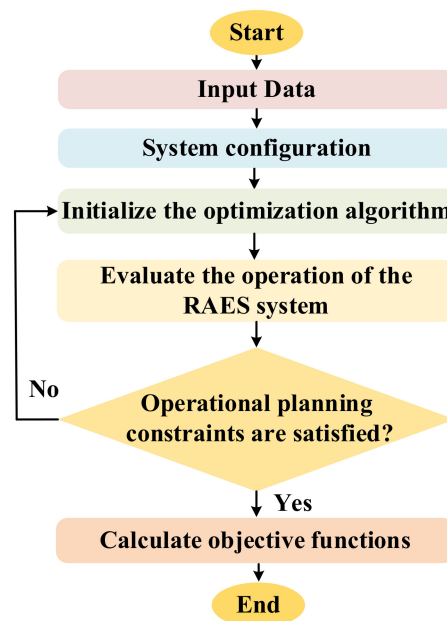
Figure 4. A generic algorithm for the optimal planning procedure of RAES systems.

The important factors in optimal planning of RAES systems are components or units, input data, objective functions, feasibility constraints, operation strategies, and optimization methodologies.

2.1. System Components

There are several system components that can be utilized for power supply in remote areas. Figure 5 classifies the components into three groups: (1) fuel-based components, (2) renewable energy components, and (3) energy storage components. The fuel-based components like diesel generators or gas generators generate power using fossil fuels and they have a high impact on greenhouse gas emission. Recently, variety of renewable energy components that can be integrated with RAES systems have been available. Solar PV, WT, hydropower, tidal power, and biogas generators are the most available and applicable components that can be applied in RAES. However, their application highly depends on the geographical location of the studied site [29]. For example, the use of tidal power is appropriate for islands. Solar PV systems have a wider application because of sun availability in most locations, easy installation on rooftops, and availability in different scales (from W to MW). The WT systems need a wide land with an acceptable wind to be installed. Hydro power needs to be installed in a location that we has access to dams or water that can be pumped from rivers to reservoirs. Biogas generators will receive more attention soon because of biomass availability in remote areas [30]. The applicable storage components in RAES systems are battery energy storage (BES), hydrogen energy, thermal storage, and flywheel. The characteristics of different types of ESSs are well explained in the literature [31].
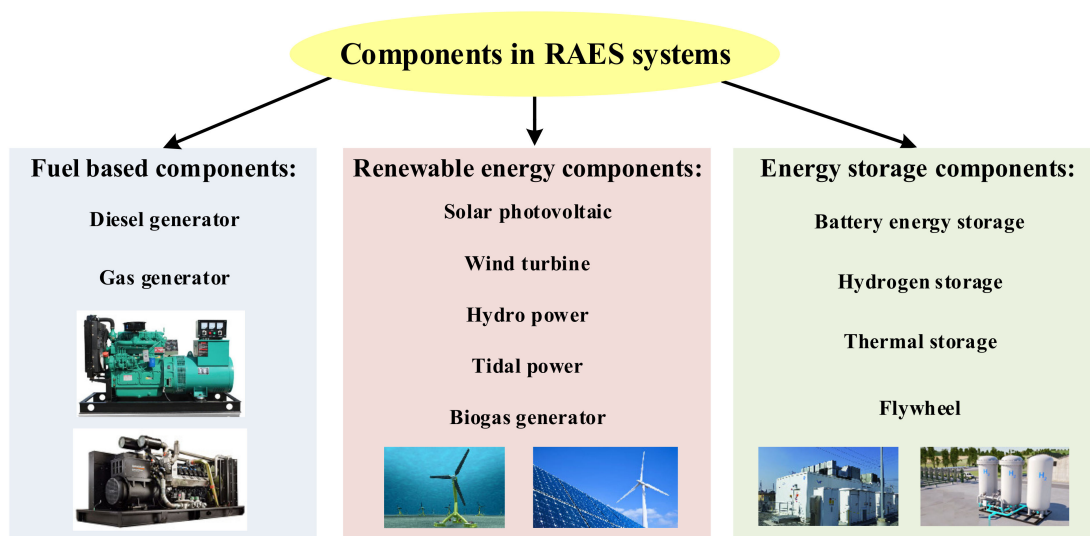
Figure 5. System components in remote area electricity supply systems.

2.2. Input Data

Figure 6 demonstrates the input data used for optimal planning of RAES systems. Technical and economic data of system components are needed based on the availability in the market of the studied country. The economic data contains the capital cost, maintenance cost, and replacement cost of the components [32]. Technical data involves the specifications like the capacity and efficiency of the components. The electricity demand should be available for a long period. The available loads for demand response should be specified in the case system if it contains demand side management. Weather data contains the ambient temperature, solar irradiance, wind speed, water availability in the reservoir, and wave speed, which like electricity demand, should be available for a long period. Project data for the study involves the project lifespan, interest/discount rate, and escalation rate of fuel. All data should be properly arranged to achieve an accurate optimal planning study. Any improper input data may result in a nonreliable and expensive system.
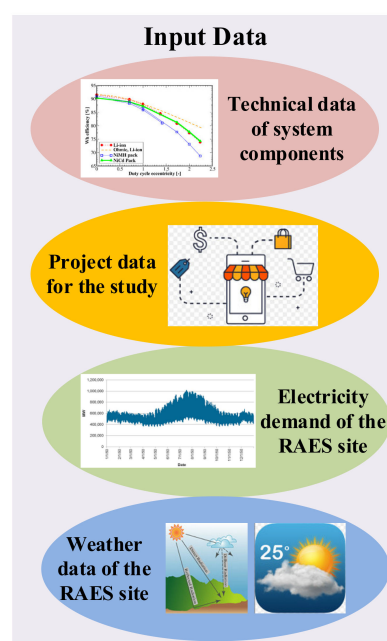

Figure 6. Input data for the optimal sizing procedure of RAES systems.

2.3. Objective Functions

The most important objective functions for the RAES optimal planning problem are demonstrated in Figure 7. Financial and reliability objective functions are the major types of targets that have been considered. The other objective functions are related to emission and some technical issues. Selection of the objective function depends on the type of study. In most of the cases, financial objective functions are the priorities. Reliability is another concern if the project financial is limited. In some cases, emission has received much attention. Due to the different natures of the objectives, optimal planning in RAES systems can be done by solving a single-objective or sometimes multi-objective optimization problem. In multi-objective problems, the results are shown in the form of Pareto fronts and a compromise between the objective functions needs to be achieved [33].
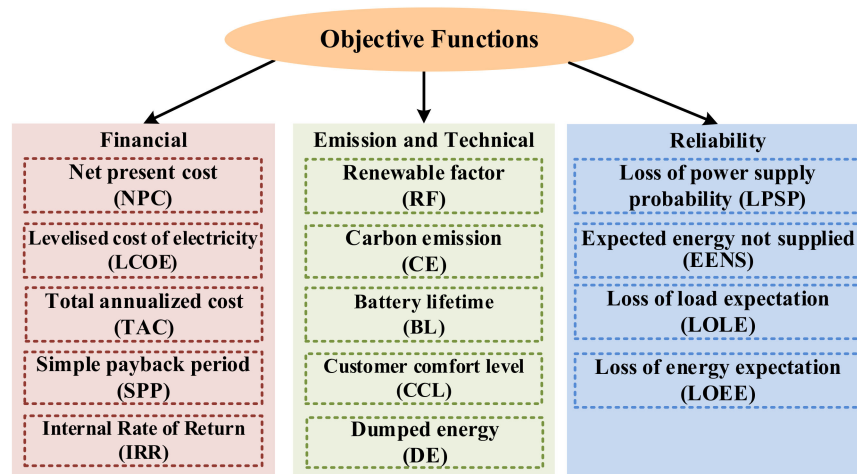

Figure 7. Objective functions for optimal planning of RAES systems.

2.3.1. Financial Objective Functions

The net present cost (NPC), levelized cost of electricity (LCOE), total annual cost (TAC), simple payback period (SPP), and internal rate of return (IRR) are the functions that can be used as financial objectives. The NPC is a summation of the total present costs of capital, maintenance, replacement, and salvage of components, as well as the present cost of fuel consumption in the case that a diesel generator is integrated [34]. The LCOE is calculated by multiplication of NPC by the capital recovery factor over the annual energy demand of the system [35]. The TAC is the sum of the annual capital and maintenance costs and annual fuel cost [36]. The SPP is the number of years to pay back the capital cost of components by the annual profits [37]. The IRR is the discount rate that makes the NPC of all cash flows equal to zero [38]. Table 1 presents the mathematical formulation of each financial objective function for the RAES optimal planning problem.

Table 1. The mathematical formulation of financial objective functions for the RAES optimal planning problem.

Objective Function	Equation	Equation Number
NPC	$f_{c1} = \min(\mathcal{NPC}) = \mathcal{NPC}_k + \mathcal{NPC}_f$	(1)
	$\mathcal{NPC}_k = \mathcal{PC}_c + \mathcal{PC}_m + \mathcal{PC}_r - \mathcal{PC}_s$	(2)
	$\mathcal{NPC}_f = \left(\frac{(1+r)^n - 1}{r(1+r)^n} \right) \times \left(\sum\limits_{t=1}^{T} \left(f(t).C_f \right) \right)$	(3)
LCOE	$f_{c2} = \min(\mathcal{LCOE}) = \frac{\mathcal{NPC}_k + \mathcal{NPC}_f}{E_p} \times \frac{d(1+d)^n}{(1+d)^n - 1}$	(4)
TAC	$f_{c3} = \min(\mathcal{TAC}) = \sum\limits_{t=1}^{T} \left(f(t).C_f \right) + \mathcal{AC}_k$	(5)

Table 1. *Cont.*

Objective Function	Equation	Equation Number
SPP	$f_{c4} = \min(\mathcal{SPP}) = \frac{\mathcal{PC}_c}{\mathcal{AP}}$	(6)
IRR	$f_{c5} = \max(\mathcal{IRR})$	(7)
	$-\mathcal{PC}_c + \sum\limits_{y=1}^{Y} \mathcal{M}_y \times (\mathcal{IRR})^y = 0$	(8)
Parameters and variables	$\mathcal{NPC}$: Total NPC of the RAES system, $\mathcal{NPC}_k$: NPC of the RAES components, $\mathcal{NPC}_f$: NPC of the fuel consumption, $\mathcal{PC}_c, \mathcal{PC}_m, \mathcal{PC}_r, \mathcal{PC}_s$: Present values of capital, maintenance, replacement, and salvation costs, f: Amount of fuel consumption, C_f: Fuel price, T: Total time period of the planning project, n: Project lifetime, r: Interest rate, E_p: Total energy demand of the RAES system, d: Discount rate, $\mathcal{AC}_k$: Annual cost of components, $\mathcal{AP}$: Annual payment of the RAES system for the external system, $\mathcal{M}_y$: is the net cash flow in year y.	

2.3.2. Reliability Objective Functions

The loss of power supply probability (LPSP), expected energy not supplied (EENS), loss of load expectation (LOLE), and loss of energy expectation (LOEE) are the most common measures and objective functions for the reliability of RAES systems. Other reliability indices that are less studied for optimal planning are the system average interruption frequency index (SAIFI) and system average interruption duration index (SAIDI). The LPSP is the probability of the unmet load over the total energy demand of the RAES [39]. The EENS is the expected energy that is not supplied by the RAES system [40]. The number of hours of the year in which the RAES load exceeds the generation system is known as the LOLE or loss of load probability (LOLP) [41]. The LOEE is the total energy not supplied by the RAES system [42]. The SAIFI is the average number of times that a system customer experiences an outage during the year project period. The SAIDI index measures the total duration of an interruption for the average customer during the project period. The mathematical formulations of the reliability objective functions for the RAES optimal planning problem are presented in Table 2.

Table 2. The mathematical formulations of the reliability objective functions for the RAES optimal planning problem.

Objective Function	Equation	Equation Number
LPSP	$f_{r1} = \min(\mathcal{LPSP}) = \frac{E_p + E_d + E_{b,ch} - E_{re} - E_f - E_{b,dis}}{E_p}$	(9)
EENS	$f_{r2} = \min(\mathcal{EENS}) = \sum\limits_{t=1}^{T} L_p . D_p$	(10)
LOLE	$f_{r3} = \min(\mathcal{LOLE}) = \sum\limits_{t=1}^{T} \sum\limits_{s \epsilon S} F_s . T_s$	(11)
LOEE	$f_{r4} = \min(\mathcal{LOEE}) = E_p + E_d + E_{b,ch} - E_{re} - E_f - E_{b,dis}$	(12)
SAIFI	$f_{r5} = \min(\mathcal{SAIFI}) = \frac{\sum \lambda_i N_i}{\sum N_i}$	(13)
SAIDI	$f_{r6} = \min(\mathcal{SAIDI}) = \frac{\sum U_i N_i}{\sum N_i}$	(14)
Parameters and variables	E_{re}: Total energy generation by renewable energy, E_f: Total energy generation by diesel generators, $E_{b,dis}$: Total discharged energy generation by battery, $E_{b,ch}$: Total charged energy generation by battery, E_d: Total dumped energy, L_p: Average annual load, D_p: Duration of unmet load, F_s: Probability of meeting state s, T_s: Loss of load duration, S: all loss of energy states, λ_i: Rate of power interruption, U_i: Duration of power outage, N_i: Number of customers for location i.	

2.3.3. Emission and Technical Objective Functions

The other groups of objective functions are emission and technical objectives, which contain renewable factor (RF), carbon emission (CE), battery lifetime (BL), customer comfort level (CCL), and dumped energy (DE). The RF shows how much of the energy demand

in the RAES system is supplied by renewable resources [43]. The CE is the amount of carbon emission by the designed RAES system during the project lifetime [44]. The BL is the lifetime of the integrated battery in RAES, which is affected by degradation. A suitable operation strategy should be developed to decrease degradation of the battery and hence increase its lifetime. The CCL is applied when the demand response is integrated in the optimal planning problem [45]. The extra energy of the DRERs and diesel generators after supplying the load is known as DE, which should be curtailed by an inverter or dumped by resistors [46]. The mathematical formulations of the emission and technical objective functions for the RAES optimal planning problem are presented in Table 3. It is notable that the formulation of CCL depends on the demand response solution in the study. For example, if load shifting is examined, then the number of hours in which the load shifting is applied can be minimized to reach the maximum CCL. The EFR can be formulated by considering the control system of inverters to minimize the power fluctuations and hence there is minimum disruption to the power supply.

Table 3. The mathematical formulations of the emission and technical objective functions for the RAES optimal planning problem.

Objective Function	Equation	Equation Number
RF	$f_{t1} = \min(\mathcal{RF}) = \left(1 - \frac{E_f}{E_p}\right) \times 100$	(15)
CE	$f_{t2} = \min(\mathcal{CE}) = \alpha + \beta \sum\limits_{t=1}^{T} P_f(t) + \gamma \left(\sum\limits_{t=1}^{T} P_f(t)\right)^2$	(16)
BL	$f_{t3} = \max(\mathcal{BL}) = 1 - D_b$	(17)
CCL	$f_{t4} = \max(\mathcal{CCL})$	(18)
DE	$f_{t5} = \min(\mathcal{DE}) = E_{re} + E_f + E_{b,dis} - E_p - E_{b,ch}$	(19)
Parameters and variables	α, β, γ: Approximate emission coefficients, P_f: Generated power by diesel generator, D_b: Battery capacity degradation due to charging/discharging cycles and environmental issues	

2.4. Feasibility Constraints

The feasibility constraints in the optimal planning problems of RAES systems are illustrated in Figure 8. There are two major types of feasibility constraints: (1) constraints associated with components and (2) technical constraints of the system.
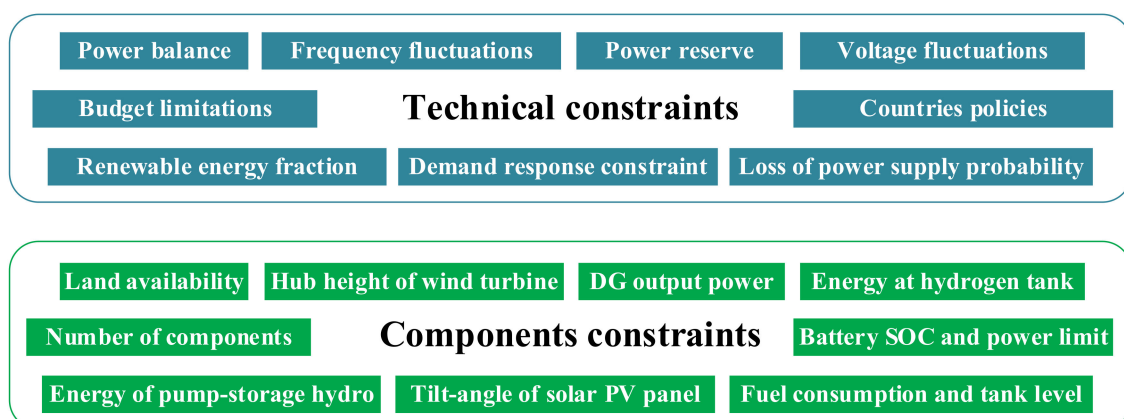
Figure 8. Feasibility constraints in optimal planning of RAES systems.

The components constraints can be related to diesel generators, DRERs, or ESSs. The constraint can be applied on the number of the components based on their unit capacity. Land availability is an important constraint to install PVs, WTs, and ESSs. The diesel generator's output power must be constrained between the minimum and maximum generation limits. The fuel consumption and tank capacity can be considered as a constraint

to limit the obtained emission from diesel generators. The hub height and blade diameter are considered as constraints to limit the size of WT. The constraint of the PV panel's tilt-angle is considered to extract higher power. There are several constraints on ESSs like the energy of the pump-storage hydro, energy at the hydrogen tank, as well as the battery SOC and power limits.

The most important technical constraint is the power balance of the RAES system, which means that the equilibrium between load and generation should be maintained. The power reserve of the RAES system should always be maintained using diesel generators or ESSs. The budget of the project to invest in the system components is an important constraint. The LPSP index can be used as a constraint to limit the amount of load curtailment. A part of the load can be limited to be supplied using the renewable generation; this is the renewable energy fraction. In some cases, the planning procedure of RAES systems is constrained by the country's policies. If demand response is applied, then constraints should be considered to limit the DR strength.

2.5. Operation Strategies

The essence of the operational strategy is to control the power flow between components and loads in the RAES system. The main aim of the operation strategies is to achieve a reliable and clean energy supply while reaching the minimum cost. The operation strategy of RAES systems is affected by several factors. The generation of renewable energy resources is the first factor. This uncertainty affects the operation of the RAES. To overcome this challenge, the forecasting data of renewable generation should be provided before making a decision for the power flow. The load consumption is another uncertainty that affects the operation. In RAES systems, prediction of the load consumption is not an easy task. Hence, the operation strategy should be carefully designed to take into account the uncertainty of the load. The state-of-charge (SOC) of the battery is a constraint that greatly affects the operation. This constraint should be accurately modelled in the RAES system operation to ensure a reliable operation. The operation strategy should consider the amount of remaining fuel in the site to decide on the best operation in the system. Another factor is the availability of suitable loads to develop demand side management in the system operation. This factor should be considered when the operation strategy considers demand response. The operational strategies of RAES systems can be classified into three groups [47]: (1) optimization model, (2) rule-based, and (3) model predictive.

2.6. Solving the RAES Optimal Planning

The optimal planning problem of RAES systems can be solved using a wide range of optimization algorithms. The most applied methods are metaheuristic algorithms. Using software to solve the problem is also evident in the literature.

2.6.1. Metaheuristic Methods

The metaheuristic methods are powerful optimization algorithms that can handle the nonlinearity and complexity of optimization problems [48]. Another advantage of metaheuristic is the ability to be used for optimal planning of single-objective and multi-objective optimization problems. A wide range of metaheuristic methods have been developed by researchers. Some of the best-known metaheuristic methods are the particle swarm optimization (PSO) algorithm, genetic algorithm (GA), and artificial bee colony (ABC).

2.6.2. Other Optimization Methods

Probabilistic, sensitivity analysis, classic mathematical, and iterative algorithms are other methods that have been used for optimal planning of components in RAES systems. Probabilistic methods have the capability to consider the unpredictability of the parameters in the optimization model [49]. The methods based on sensitivity analysis measure the sensitivity of the component's capacities against the defined objective functions in the problem [50]. In classic methods, the optimization problem is mathematically solved [51].

2.6.3. HOMER Software

Hybrid Optimization Model for Electric Renewables (HOMER) software is one of the most powerful tools for optimal planning of components in energy systems. HOMER was developed by National Renewable Energy Laboratory (NREL) [52]. The software includes a broad range of components like PV, WT, converters, diesel generator, BES, etc. To solve the optimal planning problems, HOMER minimizes the net present cost of the energy systems. HOMER software shows a wide range of results like optimal sizes, sensitivity analysis, cash flows, and other economic and technical analysis.

3. Review on Existing Studies and Technical Challenges

A review on the existing studies is conducted in this section. The studies are first classified based on their conduced case system: (1) hybrid and (2) clean RAES systems. Then, each category is classified based on the optimization model: (i) HOMER software optimization, (ii) metaheuristic methods, and (iii) non-metaheuristic (i.e., mathematical, iterative, probabilistic, etc.) methods.

3.1. Hybrid RAES Systems with/without ESS

The hybrid RAES systems are based on diesel generator power plants and renewable energy sources. The energy storage systems can also be integrated. These systems have a higher level of reliability because of the controllability of dispatchable diesel generator units. However, the emission and high cost are the main challenges. Several studies have been developed for optimal planning of hybrid RAES systems. The studies are reviewed based on HOMER software as well as metaheuristic and other methods.

3.1.1. HOMER Software for Hybrid RAES Systems

Two studies were conducted on optimal planning of hybrid RAES systems without ESS for Malaysia [53]. The optimal sizing of a diesel generator-PV-BES system was investigated in [54] for remote communities. Optimal sizing of a diesel generator-PV-WT-BES system was developed for islands [55], remote agriculture [56], telecommunication [57], and off-grid villages [58]. The diesel generator-PV-WT-FC system was optimally sized in [59] for a village and mining site. In [60], hydropower was used alongside a diesel generator-PV-WT system for optimal sizing of a rural area in Iraq. A hybrid energy storage system (BES with hydro) was optimally sized with a diesel generator-PV-WT in [61]. In [62], a biogas generation unit was optimized for a hybrid RAES system with a diesel generator-PV-WT-BES in a remote community of Bangladesh.

3.1.2. Metaheuristic Methods for Hybrid RAES Systems

The metaheuristic methods are widely used for optimal sizing of hybrid RAES systems. The existing studies of metaheuristic methods are classified based on single- and multi-objective optimization studies. Table 4 shows the reference number, applied methods, system components, RAES type, objective functions, and feasibility constraints, as well as the country and publication year of the existing studies on single-objective optimal planning of hybrid RAES with metaheuristic methods. The hybrid diesel generator-PV-WT-BES system was mostly sized by metaheuristic methods [63]. The number of components [64,65] and power balance between generation and consumption [66] were the most used feasibility constraints. In some studies, like [67], the LPSP was considered as a constraint to improve the reliability. In [68], a system with diesel generator-FT-PV-WT-BES-FW was optimized. In [69], a hydro component was added to a hybrid system. Several algorithms were examined for optimization in [70]. Renewable factor [71], unit commitment [72], and renewable energy portion [73] were also considered as the constraints for optimization.

Table 4. Characteristics of studies on single-objective optimal planning for hybrid RAES systems.

Ref.	Applied Method	System Components	RAES Type	Objective Function	Feasibility Constraints	Country	Year
[63]	Particle swarm optimization	Diesel generator-PV-WT-BES	Island village	Life cycle cost	Power balance Diesel generator output power, Battery constraint	Thailand	2011
[64]	Grasshopper optimization algorithm	Diesel generator-PV-WT-BES	Off-grid community	LCOE	Renewable energy fraction, number of components	Nigeria	2019
[65]	Harmony search algorithm	Diesel generator-PV	Remote community	NPC	LPSP, number of components	Iran	2017
[66]	Particle swarm optimization	Diesel generator-PV-BES	Rural mini-grids	NPC	Power balance, fuel consumption and tank level, curtailment of PV, energy of BES	Kenya	2016
[67]	Particle swarm optimization	Diesel generator-Biomass-PV-WT-BES	Small remote area community	LCOE	LPSP	India	2017
[68]	Particle swarm optimization	Diesel generator-FT-PV-WT-BES-FW	Remote community	LCOE	Power balance, SOC, number of components, power reserve	Australia	2020
[69]	Biogeography based optimization	Diesel generator-PV-WT-Hydro-BES	Remote home	Total cost	Number of components, power balance, SOC	India	2013
[70]	Several algorithms	Diesel generator-PV-WT-BES	Remote village	LCOE	LPSP, power balance, SOC	Egypt	2019
[71]	Hybrid simulated annealing–tabu search	Diesel generator-Biodiesel-PV-WT-BES-FC	Educational Institute	LCOE	Initial cost, unmet load, capacity shortage, fuel consumption, renewable factor, components' size	Greece	2012
[72]	Particle swarm optimization	Diesel generator-PV-BES-EV	Residential	Lifetime cost	Size of components, unit commitment constraints	India	2019
[73]	Crow search algorithm	Diesel generator-PV-FC	Remote area community	NPC	LPSP, renewable energy portion	Iran	2020

Table 5 shows the reference number, applied methods, system components, RAES type, objective functions, and feasibility constraints, as well as the country and publication year of the existing studies on multi-objective optimal planning. The emission and reliability-related objective functions were the most applied after economic objectives. In [74], RF and CE were considered together with the cycle cost as the objective functions. However, the CE and RF are in the same category of objective functions to minimize the emission and so there is no advantage in considering these two objectives for optimal sizing. In [75], the authors optimize the system based on three objective functions. The authors in [76] considered new constraints like the WT hub height and tilt angle of PV along with three objective functions. Such a study can achieve comprehensive and practical results. New metaheuristic methods like the multi-objective line-up competition algorithm [77], crow search algorithm [78], grey wolf algorithm [79], and fuzzy artificial bee colony [80] were also examined for RAES optimal sizing. The grid voltage deviation as a technical objective function was applied in [81].

Table 5. Multi-objective capacity optimization for hybrid RAES systems with metaheuristic methods.

Ref.	Applied Method	System Components	RAES Type	Objective Function	Feasibility Constraints	Country	Year
[74]	Multi-objective genetic algorithm	Diesel generator-PV-WT-BES	Not specified	LCOE, CE	Not specified	Spain	2011
[75]	Multi-objective genetic algorithm	Diesel generator-PV-WT-BES	Residential island	Cycle cost, CE, RF	SOC	China	2014
[76]	Non-dominated sorting genetic algorithm II	Diesel generator-PV-WT-BES	Island	TAC, LPSP and emission	Number of components, height of WTs, tilt angle of PV, SOC	China	2017

Table 5. *Cont.*

Ref.	Applied Method	System Components	RAES Type	Objective Function	Feasibility Constraints	Country	Year
[77]	Multi-objective line-up competition algorithm	Diesel generator-PV-WT-BES	Residential	Total TAC, total greenhouse gas	Energy of BES, power of Diesel generator, number of components, energy supply constraint	Not specified	2017
[78]	Multi-objective crow search algorithm	Diesel generator-PV-FC	Not specified	NPC and LPSP	Number of components, tank energy	Iran	2019
[79]	Multi-objective grey wolf algorithm	Diesel generator-PV-WT-Tidal-BES	Flinders island	LCOE, emission	Number of components, operating reserve	Australia	2018
[80]	Fuzzy artificial bee colony optimization mechanism	Diesel generator-PV-WT-BES	An edge region	Annualized cost, emission	Number of components, battery's energy	USA	2020
[81]	Non-dominated sorting genetic algorithm II	Diesel generator-PV-BES	Island	LCOE, CE, grid voltage deviation	Number of components, battery's energy	Indonesia	2018

3.1.3. Non-Metaheuristic Optimization Algorithms for Hybrid RAES Systems

The existing studies that optimized the capacity of components based on methodologies rather than metaheuristic and HOMER for hybrid RAES systems are categorized in Table 6. The applied method is specified for each study and the other characteristics are represented in Table 6. As illustrated in the table, various optimization techniques were used for optimal planning. The deterministic algorithm [82], iterative approach [83], new developed method [84], decision support technique [85], mixed integer linear programming (MILP) [86], triangular aggregation model [87], a new optimizer with JAVA [88], and reformed electric system cascade analysis [89] are some of the applied methods. In [90], a remote 38-bus distribution network was optimized by minimizing the annualized cost. In [91], a dynamic programming algorithm was used for optimal sizing of vanadium redox battery in a diesel generator-PV-BES system. The dynamic programming algorithm was utilized to overcome the challenge of optimal scheduling by considering the operating and efficiency characteristics of a vanadium redox battery. In [92], a stochastic mixed integer non-linear programming (MINLP) optimization was conducted for optimal sizing which was solved with GAMS software.

Table 6. Hybrid RAES system optimal planning studies with non-metaheuristic methods.

Ref.	Applied Method	System Components	RAES Type	Objective Function	Feasibility Constraints	Country	Year
[82]	Deterministic algorithm	Diesel generator-PV-WT-BES	Not specified	NPC	Power balance, SOC, number of components	Senegal	2011
[83]	Iterative approach	Diesel generator-PV-WT-BES	Residential	Energy cost	Energy of battery	Algeria	2014
[84]	Developed method	Diesel generator-PV	Campus	LCOE	Not specified	Burkina Faso	2015
[85]	Decision support technique	Diesel generator-PV-WT-BES	Remote village	NPC	LPSP	India	2007
[86]	MILP with GAMS/CPLEX	Diesel generator-PV-WT-BES	Not specified	LCOE	Minimum Diesel generator power, battery's energy, power balance	Portugal	2015
[87]	Triangular Aggregation Model and the Levy-Harmony Algorithm	Diesel generator-PV-WT-BES	Island village	COE, TAC, loss of renewable energy, LOLP, emission, LPSP	SOC, Diesel generator output power, LPSP	Australia	2018

Table 6. *Cont.*

Ref.	Applied Method	System Components	RAES Type	Objective Function	Feasibility Constraints	Country	Year
[88]	CPLEX optimizer in JAVA	Diesel generator-PV-BES	Ten households in rural area	Capacity of battery	SOC, Diesel generator's output power	Australia	2018
[89]	Reformed electric system cascade analysis	Diesel generator-PV-WT-BES	Residential community with 100 homes	Defined based on constraints	Final Excess Energy, Renewable Energy Fraction, LPSP, Annual System Cost	USA	2019
[90]	MINLP in GAMS using BARON solver	Diesel generator-PV-BES	A remote 38-bus distribution network	Annualized costs	Power flow, active and reactive power mismatch constraints, system frequency	Not specified	2019
[91]	Dynamic programming algorithm	Diesel generator-PV-BES	Not specified	Total cost per day	Power and energy of BES	USA	2015
[92]	Stochastic MINLP optimization with GAMS	Diesel generator-PV-WT-BES	Not specified	NPC	Power balance, Diesel generator constraints, operating reserve, BES constraints, budget constraint	Not specified	2018

3.2. Clean (Renewable-Storage) RAES Systems

In clean power systems, all the electricity demand of the RAES system is supplied using renewable energies and ESSs; hence, there is no diesel generator unit.

3.2.1. HOMER Software for Renewable-Storage RAES Systems

The optimal planning of renewable-storage RAES systems using HOMER software was investigated by 13 papers. The NPC was the only objective function, and the feasibility constraints were not specified in most of the studies. The PV-WT-BES system was the most considered system for clean RAES [93]. FC, supercapacitor (SC), biogas, and hydro were the other technologies used along with PV and WT in clean RAES. In [94], the optimal sizing of a PV-FC system was investigated for small communities. Hybrid energy storage systems for clean RAES systems were broadly examined. In [95], a hybrid FC-SC storage system was employed with solar PV for a remote commercial load in South Africa. A combination of BES and FC was optimally sized with PV and WT in [96]. A biogas generation unit was used with a PV-WT-BES system to build a clean hybrid system with higher flexibility in the electricity supply [97]. A biomass-biogas system was optimally sized for an agricultural farm in [98]. The application of biogas generation units with hydropower in clean RAES systems was also investigated by HOMER in [99].

3.2.2. Metaheuristic Methods for Renewable-Storage RAES Systems

The metaheuristic methods are applied as a single objective and multi objective for optimal planning of clean RAES systems. However, due to the lack of diesel generators in clean RAES systems, the emission objective functions are eliminated in the optimal planning. Table 7 presents the characteristics of the existing studies on single-objective optimal sizing of clean RAES with metaheuristic methods. Like Table 1, particle swarm optimization was the most applied algorithm. In [100], a PV-WT-BES system was optimized for a group of twenty houses. Optimizing system for a radio transmitter station was considered in [101]. In some studies, like [102], four different algorithms were used for optimal sizing to analyze the performance of metaheuristic methods. In [103,104], FC and BES were optimized, respectively, with a PV-WT system. In [105], the supply of thermal loads was also considered along with the electric loads using a PV-thermal system. In [106], a backup natural gas boiler was also optimized along with a renewable system. A bio-diesel component was optimized in [107]. A renewable system was optimized for a remote house in [108]. In [109,110], two new methods known as hybrid grey wolf optimizer-sine

cosine algorithm and improved bee algorithm were utilized. Particle swarm optimization was used to optimize PV-WT-BES and Biogas-PV-WT systems in [111,112], respectively. Tidal power was used along with PV-WT-FC system in [113]. In [114], four optimization algorithms were compared. In [115], a PV-WT-PHS system was designed to supply the loads in a coastline community. Such a system is very efficient in coastline communities due to water availability for PHS.

Table 7. Single-objective metaheuristic capacity optimization for clean RAES systems.

Ref.	Applied Method	System Components	RAES Type	Objective Function	Feasibility Constraints	Country	Year
[100]	Firefly-inspired algorithm	PV-WT-BES	Group of twenty households	COE	Energy of battery, number of components, load dissatisfaction rate	Algeria	2017
[101]	Water cycle algorithm	Biogas-PHES-PV-BES	Radio transmitter station	NPC	LPSP, number of components, SOC, upper reservoir volume	India	2019
[102]	Four algorithms	PV-WT-BES PV-WT-FC	Not specified	TAC	Number of components, energy of tank and battery	Iran	2014
[103]	Flower pollination optimization algorithm	PV-WT-FC	Rustic	NPC	Number of components	Egypt	2020
[104]	Genetic algorithm	PV-WT-BES	Remote community (2240 home with 4440 population)	NPC	SOC, EENS	India	2016
[105]	Discrete harmony search	MHP-Biogas-Biomass-PV-WT-BES	Remote rural households (723 homes with 3031 population)	TAC	Unmet load, number of components, energy of BES	India	2017
[106]	Particle swarm optimization	PV-thermal, WT, microturbine, thermal storage, backup natural gas boiler	Not specified	TAC	LPSP, SOC of energy storage systems, thermal power, number of components	Iran	2019
[107]	Hybrid harmony search and simulated annealing algorithm	Bio Diesel-PV-WT-BES	Five typical residential building	Life cycle cost	Number of components, power balance, SOC	Iran	2018
[108]	Particle swarm optimization	PV-WT-Tidal-BES	Remote house	NPC	Number of components, reliability, SOC	France	2019
[109]	Hybrid grey wolf optimizer-sine cosine algorithm	PV-WT-FC	Residential-commercial center	lifespan cost of hybrid system	Load interruption probability, number of components, energy at tank	Iran	2020
[110]	Improved bee algorithm	PV-WT-BES-FC-Reverse Osmosis Desalination	Desalination systems and community load	Total life cycle cost	LPSP, energy at hydrogen tank, SOC, number of components	Iran	2018
[111]	Particle swarm optimization	PV-WT-BES	Single house	NPC	Power balance, number of components	Australia	2019
[112]	Particle swarm optimization	Biogas-PV-BES	Residential	LCOE	Constraint on deficit power of PV	Kenya	2017
[113]	Whale optimization algorithm	PV-WT-FC-Tidal	Remote region	NPC	Load deficit probability Size of components	Iran	2020
[114]	Four algorithms	PV-WT-BES-PHS	Remote island	NPC	Number of components, battery's energy and SOC	China	2020
[115]	Genetic algorithm	PV-WT-PHS	Coastline communities	Life cycle cost	Not specified	Nigeria	2020

The existing studies on RAES optimal planning with multi-objective methods are categorized in Table 8. The multi-objective particle swarm optimization algorithm was the most applied method. Objective functions like volatility [116], and dumped energy (DE) [117], were considered in the existing studies. In [118], the PV-WT-BES system was combined with pumped hydro storage (PHS). A combination of FC and BES was considered in [119]. A range of economic and reliability objective functions were applied. Most of the studies optimized the capacity of three components: PV-WT-FC [120], PV-WT-PHS [121], PV-WT-BES [122], PV-WT-FC [123], and PV-BES-FC [124]. Only [125] optimized a PV-BES system with two components.

Table 8. Clean RAES systems optimal planning with multi-objective metaheuristic methods.

Ref.	Applied Method	System Components	RAES Type	Objective Function	Feasibility Constraints	Country	Year
[116]	Multi-objective particle swarm optimization	PV-WT-BES	Residential	LPSP, LOEP, volatility, life cycle cost	Number of components	China	2017
[117]	Multi-objective grey wolf algorithm	PV-WT-BES	Rural telecom tower	COE, LPSP, DE	SOC	India	2020
[118]	Multi-objective grey wolf algorithm	PV-WT-BES-PHS	Isolated farmstead	COE, LPSP	Energy of battery and pump-storage hydro	Algeria	2019
[119]	Multi-objective genetic algorithm	PV-WT-BES-FC	Not specified	NPC, excess energy, life cycle emission	Number of components, energy of tank	Australia	2015
[120]	Imperial competitive algorithm	PV-WT-FC	Not specified	Total cost, emission	Equivalent loss factor, angle of PV array, number of components, energy stored at tank	Iran	2015
[121]	Multi-objective particle swarm optimization	PV-WT-Hydro-PHS	Not specified	LPSP, LCOE, curtailment rate of wind and PV power	Not specified	China	2020
[122]	Multi-objective genetic algorithm	PV-WT-BES	A residential home with four occupants	Life cycle cost, embodied energy, LPSP	SOC	USA	2014
[123]	Multi-objective particle swarm optimization	PV-WT-FC	Not specified	TAC, LOEE, LOLE	Energy at tank, number of components, PV tilt angle	Not specified	2016
[124]	Non-dominated sorting genetic algorithm II	PV-BES-FC	Residential (10 houses)	LPSP, system cost, potential energy waste	Number of components	China	2019
[125]	Mutation adaptive differential evolution	PV-BES	Rural area	Life cycle cost, LOLP, LCOE	SOC	Malaysia	2020

3.2.3. Non-Metaheuristic Optimization Algorithms for Renewable-Storage RAES Systems

Table 9 lists the characteristics of the studies on capacity optimization for clean RAES systems with other methods rather than HOMER and metaheuristic methods. To solve the multi-objective problem by the methods rather than metaheuristic approaches, the ε-constraint method [126], hybrid multi-criteria decision-making method [127], sensitivity analysis [128], Simulink design optimization [129], iterative technique [130], power pinch analysis [131], object-oriented programming [132], probabilistic simulation [133], cascade calculation [134], enumerative method [135], and pattern search optimization [136] were developed by the existing studies. In [137–139], iterative based optimization was applied for optimal planning. A PV-WT-BES system was optimized for a remote area mountain lodge [140], a remote community [141], and a forestry camp [142]. A concentrating solar power (CSP) plant was combined with WT and BES in [143]. Sensitivity method was used to optimize a PV-WT-FC-PHS in [144].

Table 9. Existing studies on optimal planning of clean RAES systems with non-metaheuristic methods.

Ref.	Applied Method	System Components	RAES Type	Objective Function	Feasibility Constraints	Country	Year
[126]	ε-constraint method	PV-WT-BES-FC	Not specified	NPC, LPSP, DE	SOC, energy in hydrogen tank, number of components	Not specified	2018
[127]	Hybrid multi-criteria decision-making method	PV	Water pumping	Life cycle cost, LOLP, excess water volume	Not specified	Malaysia	2018
[128]	Sensitivity analysis	PV-WT-BES-PHS	Remote island	Life cycle cost	Not specified	Hong Kong	2014
[129]	Simulink Design Optimization	PV-BES-FC	Not specified	Cost	Not specified	Spain	2013
[130]	Iterative technique	PV-WT-BES	Remote residential household	LPSP and LCOE	SOC, number of components	Algeria	2011
[131]	Power Pinch Analysis	PV-BES	Remote community	Cost	Not specified	Bhutan	2017
[132]	Object-Oriented Programming	PV-WT-BES	Not specified	NPC	LPSP, SOC	Algeria	2014
[133]	Probabilistic simulation	PV-BES	A refrigerator used for medical supply in remote area	Loss of load hour, energy not supplied	Not specified	USA	1998
[134]	Linear programming based on a cascade calculation	PV-WT-Tidal-BES	Island	Equivalent loss Factor	SOC	France	2016
[135]	Enumerative method	PV-BES	House	LCOE	Unmet load percentage, number of days of autonomy	Spain	2018
[136]	Pattern search-based optimization	PV-WT-BES	Not specified	Total system cost	SOC, load constraint for DR, EENS, energy index of reliability	USA	2014
[137]	Iterative method in MATLAB	PV-WT-BES-FC	Pumping system (centrifugal pump)	Deficiency Power Supply, NPC	SOC, tank energy	Tunisia	2018
[138]	Iterative simulation-optimization	PV-WT-BES-FC	Not specified	LCOE	LOLE	Iran	2016
[139]	An iterative method	PV-WT-BES	Ten houses in a remote island	NPC	LPSP, COE	China	2019
[140]	MILP	PV-WT-BES	Remote area mountain lodge	NPC	Energy of BES, power balance	Italy	2020
[141]	Logical approach	PV-WT-BES	Remote community	NPC	Number of components	South Korea	2016
[142]	MILP with CPLEX solver in GAMS	PV-WT-BES	Forestry camp	NPC	BES energy and charge/discharge, demand response constraint	Iran	2017
[143]	Stochastic optimization	WT-concentrating solar power (CSP) plant-BES	Island	Overall cost	SOC, power balance, output power of components	China	2020
[144]	Sensitivity based method	PV-WT-FC-PHS	University	RES fraction	Not specified	Cyprus	2020

3.3. Discussion

Regarding the used objective functions in the existing studies, the priority goes to the cost objectives in most of the studies. Then, the reliability objectives have received more attention than the emission aims because of the grid's absence in remote areas' systems.

Finally, due to global concern, emission objective functions have received enough attention from researchers after the cost and reliability targets.

The number of publications per continent for RAES optimal planning is demonstrated in Figure 9. It is observed that most of the studies (about 100 papers) were conducted for Asian case studies. After Asia, optimal planning for African case studies has attracted the greatest attention with more than 30 papers. Figure 9 also shows the number of publications per country in Asia. It is observed that a high contribution of studies were developed in Iran and India. China is the next country with about 15 studies on RAES optimal planning.
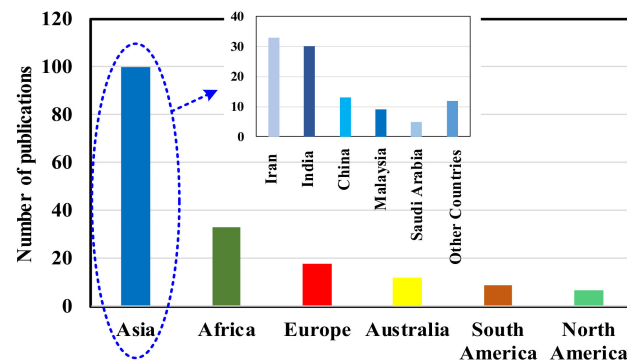
Figure 9. Number of publications per countries for RAES optimal planning.

3.3.1. Electricity Supply Cost for RAES Systems

Conventionally, the power of RAES grid is supplied by diesel generators. Because of the high fuel price and the transportation problem, the cost of electricity supply by the diesel generators is high. When the renewable energy resources were introduced, the price of the components was high. However, due to the technology maturing, the price of the renewable components has dropped, and they are now competitive with the diesel generator. Most of the studies have shown that including renewable energy components can decrease the cost of the electricity supply for RAES systems. For example, in [68], it was addressed that adding PV and WT to the diesel generators in RAES systems decreases the electricity cost slightly. However, adding a battery energy storage system can significantly decrease the electricity cost. In [145], it was found that adding flywheel storage is not economical for integration with renewable energy in RAES systems. It was illustrated in [146] that a clean renewable-battery system is competitive with diesel generator systems.

3.3.2. Discussions on Methods

Metaheuristic methods have been broadly used for optimal planning of RAES systems because of their good potential to escape from the local optimal point, freeness from gradient calculation, and simple implementation. These methods could effectively prevail over the nonlinearity and complexity of optimization formulation. The other merit of these algorithms is the capability to deal with non-convex optimization problems that is hardly possible when classical methods are utilized. The metaheuristic methods have the capability to reach the near-optimal solutions effectively. Since the problem of optimal planning with several components deals with the fact that many results may be found as possible solutions, it may not be required to find the exact optimal result and hence, the near-optimal result by satisfying the design constraints can be a potential solution. The literature has reported that more than 70% of the existing papers have used metaheuristic methods for RAES optimal planning.

As the number of objectives has increased, solving the optimal planning problem of an RAES system from a multi-objective basis has become more popular. On the other hand, the number of constraints is also increased, and the types of constraints become more complicated. Hence, the multi-objective metaheuristic methods can be used as an appropriate method for such problems. These methods are able to generate several

solutions in form of a Pareto front in each run of the simulation. This is the main advantage of multi-objective metaheuristic methods over the classic methods. The multi-objective genetic algorithm is the most applied method for multi-objective optimal planning.

Using HOMER software, NPC is the only objective function that was considered by all existing studies. The main deficiency of using HOMER is that the objective function cannot be changed. The design constraints are improvised in the block of the components and the designer cannot define new constraints or models. This is the main reason that the design constraints are not specified in most of the studies by the HOMER. Another deficiency by HOMER is the incapability to run multi-objective optimization. However, due to the simplicity of the software, HOMER is widely used for RAES systems planning.

Among the non-metaheuristic methods, solving the RAES optimal planning problem with MILP using commercial software was the most utilized one. In such a method, the mathematical formulation of the problem is modelled. A high computational burden and inability to handle the nonlinearities are the main shortcomings of such classic methods. The iterative methods may be trapped in local solutions and hence the global optimal solution may not be attained. To overcome this challenge, the iterative approach should be repeated multiple times by random initial conditions. Hence, the best local solution obtained by the approach is chosen as the optimal solution. It should be noted that repeating the simulation for different initial conditions increases the calculation time of the approach.

Analytical approaches evaluate the performance of the system for a set of feasible configurations for the specific capacity of the components in the RAES system. Then, the best system configuration is selected by evaluating single or multiple performance indices. Probabilistic methods develop suitable models for the generation of resources and/or load demand and they create a risk model by a combination of the developed models. The probabilistic methods for the planning of RAES systems were used by a few studies. This is because the probabilistic methods cannot characterize the dynamic changing nature of hybrid or integrated RAES systems.

3.3.3. Technical Challenges

Although a considerable number of studies have been conducted on optimal planning of RAES systems, several challenges exist in the present status that should be discussed. These major challenges can be highlighted as follows:

- High capacity of BES in clean remote area energy supply systems.
- Demand response strategies for optimal planning in RAES systems.
- Robust optimal planning of components for clean RAES systems.
- Neglecting guidelines for customers in RAES systems.
- Neglecting distribution network constraints in the optimal planning model.

Due to the intermittency of renewable energy, a large mismatch may happen between generation and consumption in clean RAES systems. To compensate the power deficiency, a large capacity of BES is required. This high capacity of the battery is a technical challenge due to the high cost of the battery. To reduce the capacity of the battery, demand response programs should be developed [147]. Although the DR strategies have been developed for grid-connected systems [148], the application of DRs in optimal planning of remote areas systems was neglected. Due to the high intermittency of renewable energies and load, a robust optimal planning of a clean RAES system can guarantee the energy supply. However, a robust optimal planning in the RAES system was neglected. Guidelines for customers in RAES systems to purchase PV, WT, and BES were neglected in the existing literature. If customers are equipped with renewable-storage systems, the high pressure of the energy supply can be efficiently reduced in RAES systems. Only limited studies considered some distribution network indices in the planning process of RAES systems. However, the distribution network constraints like voltage and frequency constraints can greatly affect the optimal planning problem [149].

4. Recent Developments

Recently, some research developments have been achieved for optimal planning of RAES systems, which are discussed in this section.

4.1. EV Charging Stations and Diesel Generator

In [150], an optimal sizing methodology was developed for allocation of EV charging station and DGs in a remote community. A multi-objective optimization problem was developed to minimize the emission and cost of the microgrid. It was assumed that by substituting fossil-fueled vehicles with EVs, the pollutant emissions from driving would be zero. It was found that it will be both economic and environmentally friendly for investors to construct EV charging stations in remote communities.

4.2. Integrated Energy System with Solar PV and Biogas

In [151], optimal sizing of an integrated energy system with solar PV, battery, and biogas was proposed for a remote area residential load. The main purpose of adding the biogas system was twofold: (1) to decrease the capacity of the battery, and (2) to design a system for thermal, electricity, and gas supply in remote areas. The study showed that the proposed system resulted in a low LCOE for the case study. Such studies, by considering a multi-energy system for remote areas, reccomend to not only supply the electricity but also the thermal and gas demands.

4.3. Hybrid Energy Storage and PV

In [152], a standalone system was developed based on solar PV, ice-thermal energy storage (TES), and BES for an islanded building. This study achieved two valuable developments: first, optimal planning of an RAES system; and second, deployment of the dynamic model of the system to show the system operation in real-time simulation on the OPAL-RT platform. A coordinated operation between BES and TES was proposed to decrease the capacity of BES. It was found that the system based on hybrid energy storage is more economical than the system with only BES. Such studies are valuable for RAES systems to validate both the planning and operation of the system.

4.4. Optimal Configuration

In [153], optimal sizing of standalone microgrids was modelled with full identification of the system topology. In this model, the optimal type of microgrid (AC, DC, or hybrid AC/DC) as well as the capacity optimization of the DGs, storages, capacitors, and power electronic converters were assigned by minimizing the total sizing cost. If a hybrid topology was found as the best configuration, the model calculated the optimal size of interlinking converters. By considering the control, sizing, and topology of the RAES system, such studies are of interest.

4.5. Accurate Battery Lifetime Estimation and Technology Selection

In [154], a two-stage methodology was developed to determine the optimal capacity, maximum depth of discharge, and the service lifetime in years of BES for a remote microgrid. The different performance of full and half cycles was investigated. It was found that the higher capacity of BES results in lower DODs and hence a higher estimated lifetime for RAES microgrids.

4.6. Concentrating Solar Power Plant

In [143], a renewable-storage system was proposed for a remote area electricity and water supply system based on a WT, concentrating solar power (CSP) plant, and BES. By using the CSP plant, superheated steam was generated to run generators to produce electricity. The low/medium-temperature exhaust steam of the CSP was used in desalination units to produce freshwater. A TES was also considered in the CSP plant to reduce the BES

capacity. An integrated CSP-desalination unit could be very useful for RAES systems. Such a system would give more flexibility for energy scheduling.

4.7. Cooperation of a Diesel Generator and Flywheel with Incentive DR

In [155], the flywheel (FW) was examined for optimal planning of the RAES system. The authors optimized a diesel generator-FW-PV-WT-BES system by considering an incentive DR program. The FW reduced the number of offline diesel generators to supply the loads. By the incentive DR, customers received a financial benefit to contribute to load shedding. The study provided some good views on the optimal sizing problem; however, a flat incentive was selected.

5. Future Scopes

This paper facilitates future scopes on the optimal planning of RAES systems. The future scopes are discussed in this section.

5.1. Incentive Demand Response

An incentive DR in a clean RAES system can be an efficient strategy to decrease the battery capacity and hence the electricity cost of the system. In such a strategy, the customers are incentivized to reduce, shift, or curtail their load demand. The time of the DR can be changed based on the forecast data of renewable generation and load consumption. For example, on cloudy days, a high battery charge is required to compensate for the lack of solar generation. To reduce the required battery charge, some of the load demand can be curtailed by an incentive payment to the customers. Using this strategy, the capacity of the battery is automatically decreased. Incentive DR was not investigated properly in the existing studies, and it is a potential research area for the future.

5.2. Distribution Network Constraints

Optimal planning of RAES systems by considering distribution network constraints obtains more practical results. Generally, the households are located far from each other in remote and rural areas, which causes long distribution lines between customers in RAES systems. Hence, the distribution network in an RAES system needs more attention due to power losses as well as voltage and frequency deviations [156]. The optimal planning should be accomplished by considering all distribution constraints. The optimal allocation of components should be investigated in an RAES system by considering the distribution network and components requirements.

5.3. Considering Voltage and Frequency Control

New studies can be conducted by considering the voltage and frequency control of the components in the RAES systems. This should receive greater attention for the recent RAES systems because of the higher contribution of DRERs with inverter interfaces. For example, the dumped power has been investigated in several studies as a constraint or objective function. However, how the inverter of DRERs can control the dumped power was not mentioned. An efficient way to approach this challenge is to first optimize the capacity of the components and then validate the optimal system through hardware-in-the-loop testing.

5.4. New Software Tools for Optimal Planning of RAES Systems

The only available software for RAES systems' optimal planning is HOMER. However, HOMER software suffers from a range of limitations. For example, the only type of objective functions that can be applied in the optimal planning process with HOMER are financial objectives. On the other hand, the operation of the system cannot be changed in HOMER. Therefore, new software for optimal planning of RAES systems with the capability of using different objective functions, applying multi-objective optimization, and flexible operation

strategies are of great interest for future perspectives. The new software should also be able to develop demand response strategies due to smart grid developments.

5.5. Guidelines for RAES Customers

Guidelines in RAES systems should be rendered for the customers to purchase renewable-storage systems. The guidelines can help electricity consumers to invest the right cost in solar PV, WT, and BES for their properties [157]. The guideline can be based on the budget, the available rooftop for PV installation, the available land for WT, and the possibility of DR application. Such guidelines can reduce the electricity cost and increase the reliability of the electricity supply of customers in RAES systems.

5.6. Feed-in-Tariff in RAES

An effective incentive for the customers in RAES systems is to assign feed-in-tariff for exporting electricity from their PV and WT systems to the distribution network. The feed-in-tariff can be based on the flat rate or time-of-use rates [158]. When the feed-in-tariff is assigned, the customer exports the power to supply the electricity demand of the other electricity consumers in the system. Using the feed-in-tariff, the electricity bill of the customers is reduced and the high pressure of the electricity supply by the main grid will be lifted. An efficient feed-in-tariff program for customers in RAES systems is a good policy in the future.

5.7. Robust Optimal Planning

To achieve a clean reliable RAES system to supply the load uninterruptedly, a robust optimization is essential. Optimal planning with robust strategies can overcome the intermittency of consumption and generation sides as well as the demand variations subjected by population change. The robust strategies can consider the worst-case scenario of renewable generation and load consumption to generate the optimal capacities [159]. Due to the robustness of these methods, the designed system can supply the load in the days with lower renewable generation and higher load variations. Robust optimal planning of a clean RAES system is an efficient future direction.

5.8. Resilient Optimal Planning

The resiliency of an RAES system is the ability to withstand grid outages (low-frequency high-impact incidents) significantly while ensuring the minimum possible interruption in the supply of electricity and enabling a quick restoration of the system to the normal operation. Resiliency is an important issue that can be considered in the planning stage of RAES systems. Grid outages may happen in RAES systems due to several reasons. The power supply of a conventional RAES system is generally vulnerable due to the lack of diversity in the types of available power generation resources. On the other hand, since the RAES systems are located far from service centers, it takes time to send service teams for maintenance. Therefore, the probability of electricity outage should be considered in the planning stage. This topic has been ignored in the literature for RAES optimal planning. Hence, it is a potential study area for researchers.

6. Conclusions

This paper investigated the state-of-the-art optimal planning of remote area electricity supply (RAES) systems. The existing studies on the field were classified based on hybrid or clean systems, optimization methodologies or software optimization, and as single- or multi-objective problems. The existing challenges were explained and the latest developments in the optimal planning of RAES systems were discussed. The future perspectives were introduced to highlight potential research ideas for researchers. The main findings of this review paper can be briefly explained as follows:

It was found that feed-in-tariffs (FITs) should be introduced for customers in RAES systems. This increases the penetration level of distributed renewable energy resources in

RAES systems. By the FIT, the customers can sell their extra power to the RAES grid in order to reduce the electricity cost.

New software tools are necessary to optimize the capacity of components based on various objective functions. The current tools like HOMER software cannot solve multi-objective problems. In addition, it is not easy to implement demand response strategies. Hence, new software can be introduced by giving more flexibility to the designers for optimal planning of RAES systems.

The inclusion of guidelines for RAES customers is a positive point of this paper. Indeed, the identification of guidelines would be expected as a tangible result of this review. The guidelines can help the customers to select the best capacity of renewable resources and energy storage systems to achieve the minimum emission and energy bills.

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