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REVIEW ARTICLE

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State-of-art review of the optimization methods to design the configuration of hybrid renewable energy systems (HRESs)

Abstract The current research aims to present an inclusive review of latest research works performed with the aim of improving the efficiency of the hybrid renewable energy systems (HRESs) by employing diverse ranges of the optimization techniques, which aid the designers to achieve the minimum expected total cost, while satisfying the power demand and the reliability. For this purpose, a detailed analysis of the different classification drivers considering the design factors such as the optimization goals, utilized optimization methods, grid type as well as the investigated technology has been conducted. Initial results have indicated that among all optimization goals, load demand parameters including loss of power supply probability (LPSP) and loss of load probability (LLP), cost, sizing (configuration), energy production, and environmental emissions are the most frequent design variables which have been cited the most. Another result of this paper indicates that almost 70% of the research projects have been dedicated towards the optimization of the off-grid applications of the HRESs. Furthermore, it has been demonstrated that, integration of the PV, wind and battery is the most frequent configuration. In the next stage of the paper, a review concerning the sizing methods is also carried out to outline the most common techniques which are used to configure the components of the HRESs. In this regard, an analysis covering the optimized indicators such as the cost drivers, energy index parameters, load indicators, battery's state of charge, PV generator area, design parameters such as the LPSP, and the wind power generation to load ratio, is also performed.

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1 Introduction

In the present time, the traditional sources of power such as fossil fuels, coal, natural gas, and petroleum are becoming scarcer owing to the significant growth of the energy demand in the commercial, industrial, agricultural and domestic sectors. On the other hand, the significant dependency on such sources of energy, which emerged in the previous decades, has undoubtedly led to a considerable depletion in their resource. Another important matter is related to the interference of the global warming, climate change and the associated environmental pollutions with our global environment, which has caused devastating effects on the human life as well as the earth during the recent decades. Therefore, there has been a significant motivation and interest in the development of clean sources of power. Renewable energy sources such as wind, solar, and biomass, which have received a growing attention from many firms and policy planners around the globe, are being considered for utilization and electrification in many geographical locations of the world. The hybrid energy systems which incorporate such sources are typically capable of electricity production for several applications such as commercial or office buildings, rural areas with difficult access to electricity, hospitals, telecommunication services, and many other facilities. In such systems, energy is produced using primary power system components, such as the WECSs, PVs, hydro power systems, and/or other conventional generators, which employ fossil fuel-based generators such as the DG. Hybrid power systems, in terms of their energy production, are generally ranged from small to large scales. They are capable of generating electricity for small residences to commercial scale systems, which can electrify a whole village or an island. Hybrid power systems have been designed many years before with the purpose of energy production and electrification for many remote areas as well as different commercial buildings, particularly in locations where the electricity grid, according to the techno-economic considerations, is not viable [1].

Taking into account the cost, reliability and efficiency of power systems, as their important criteria, an HRES, compared with only one source of energy, offers a much better solution. There are many types of hybrid power system configurations, which can be economically viable subject to the demand and the availability of a resource in a proposed area. Typically, in the occasion that the solar resource of a region is strong and significant enough, wind speed values may be in low levels. The opposite situation may also be correct. Furthermore, it is worthwhile mentioning that, for remote regions where the possibilities of accessing to the national electricity grid is slim to none due to the techno-economic restrictions, HRESs are seen as a great alternative and they are therefore proposed in many locations around the globe. For the purpose of enhancing their efficiency, other energy sources such as fuel cells, hydrogen, and the DG, can also be included in the configuration of the system. This will support the system by supplying more energy requirements for an area, which has difficulty in accessing to electricity, and national grid.

It is important to bear in mind that there are particular advantages contingent upon the configuration of the HRESs. A WT/PV system, for instance, can generate more electrical power output from the wind during the winter time, while further peak energy output can be yielded from solar arrays during the summer time. A WT/Hydro system has the merit of generating electrical power by releasing it into a hydropower plant when it is required. This would particularly be useful for islands which are not connected to larger grids. Nevertheless, HRESs, despite their primary advantages, suffer from a few drawbacks with regard to their design and operation process. Table 1 summarizes a few characteristics of the HRESs in terms of their positive and negative sides. Clearly, as it has also been proven by previous research, despite a few points which arise from the design process of the HRESs, the advantages of the HRESs greatly outweigh their drawbacks, thereby making them a much more interesting and viable solution to exploit the sustainable sources of power in regions with power shortage problems.

With reference to the capacity sizes of the HRESs, it is important to notice that they typically have a wide range of capacity sizes from kilowatt to hundreds of kilowatt based on the load, which can serve. Small-scale hybrid power systems which typically have a capacity lower than 5 kW can meet the load demand of a remote house, a telecommunication relay system, or any small-scale system. Medium-scale hybrid power systems with a capacity rated from five to hundred kW can be adequate alternatives to electrify areas with more considerable number of residences and families, or other community facilities. These hybrid systems sometimes can be connected to the grid, if they are close to a national utility grid. However, in most occasions, their operation is standalone. At last, the large-scale hybrid power systems which typically have a capacity of larger than 100 kW are linked to the electricity grid to permit transferring electricity from the grid to the hybrid power system and vice versa. This situation happens when the electricity surplus of the system is considerable. In Table 2, the HRESs are classified based on their size.

It does not hurt to bear in mind that the key drivers for enhancing the utilization of renewable sources of energy are linked with their large and unexplored potential, which are typically considered as a substantial factor for enhancing the gap among the demand and supply, and in order to improve sustainable sources of power and reduce environment concerns.

The maximum available potential in the majority of the locations around the globe are primarily wind and solar energy, nevertheless wind and solar resources are heavily contingent upon climatic conditions, and they are not, therefore, adequately predictable. Therefore, owing to the stochastic nature of these sources, by way of an example, designing a system based on only wind energy, in a small-scale situation, may not be technically or economically viable. Therefore, a combination of multiple renewable energy sources is fascinating researchers to encourage and design such power systems leading to making such power systems more reliable and cost-effective. Thereby, research and development in the field of solar, wind, and other renewable energy sources will be a great future substitute for meeting the electrical demand and supplying the deficiency of power. However, it is worthwhile to mention that, due to the stochastic nature of renewable sources of

Table 1 General advantages and disadvantages of the HRESs as demonstrated by previous research

Advantages	Disadvantages
Utilization of the natural and renewable sources	Dependency on the natural cycles
Low level of O&M costs	Initial costs of these systems are higher than comparably sized traditional generators
No pollution or wastes produced by the natural sources	Relatively high costs
Minimizing the intermittency	The peak-loads cannot be managed well without energy storage
Lower atmosphere contamination	Complexity of the design procedure
Fuel saving	Monthly fee charge

Table 2 Classification of the HRESs on the basis of their size

Type	Size	Typical load
Small-scale	Lower than 5 kW	Suitable for remote homes or telecommunication systems
Medium-scale	Between 5 and 100 kW	Remotely located communities
Large-scale	Upper than 100 kW	Regional loads

power, such issues may lead to invariabilities in the power output, making the design and optimization of the HRESs even a bit more complicated. For this purpose, nowadays, the optimization of HRESs has become immensely important, playing a substantial role for their design, configuration, and reliability.

1.1 A brief literature review concerning the design of the HRESs

In recent years, progress and attention toward the development of the HRESs has become notably considerable. Many researchers around the globe have proposed innovative models to enhance the configuration of these systems in different innovative ways. To perform a careful review, a series of results obtained in the literature review have been evaluated to arrange and structure an inclusive table of classification.

To shed some light on why the HRESs have become increasingly popular, a brief review of the literature demonstrates the great motivation of researchers, policy planners, and stake holders to significantly invest on such high-efficient power systems, and to devise innovative solutions, and optimization methods for better enhancement of such systems.

About 15 years ago, El-Hefnawi [2], with the help of the Fortran programming language, proposed a novel mathematical modeling technique to estimate the minimum number of storage days and PV array area by taking into account the pre-operating time of the DG, as one of the main design variables of the HRESs. In the same year, Shrestha and Goel [3] proposed a novel approach to determine the most efficient configuration of the PV array sizes and battery in order to satisfy the demand load of the system. In 2007, Ashok [4] developed a novel hybrid power system by using different components to find out an optimized configuration of each of the components by employing a nonlinear optimization algorithm, which had constraints and limitations. The HRES configuration proposed, which integrated the PV panels with a DG system, was fueled by animal manure. In a research conducted in 2013 [5], a multi-objective optimization model for a grid-connected hybrid power system with configuration of PV panels, DG, and the storage system with the aim of minimizing the life cycle costs and decreasing the carbon dioxide emissions of the hybrid power systems was introduced. In a research performed in 2016 [6], a novel HRES model to enhance and optimize the customized power systems, using a Matlab-based tool, entitled “Matlab/Sim Power System™,” was introduced, and presented. In the same year, Shafiullah [7] designed an integrated HRES system to speed up and ease the transmission of considerable power production. Chauhan and Saini [8] conducted a comprehensive research study by employing a techno-economic optimization approach for energy management of a stand-alone integrated renewable energy system for utilization in remote areas of India. Bordin et al. [9] presented a linear programming approach to perform analysis of the battery degradation and its optimization for the off-grid power systems with integration of solar power. The main contribution of this study was to develop a method to include battery degradation processes inside the optimization models.

There have also been many other research studies which aim to examine the sensitivity analysis, as well as the optimization of the HRESs configuration through employing new advanced methods. In such research works, the utilization of the clean sources of power through diverse ranges of the mathematical, and the optimization methods has been outlined [10–16]. Furthermore, there are also many other research works demonstrating the importance of renewable sources of energy [17,18]. Ramazankhani et al. [19] investigated utilization of the geothermal energy source for producing hydrogen energy, which was considered as a unique research in this regard. Zarezade and Mostafaeipour [20] performed a study for identifying factors, which affected implementing solar energy in Yazd, Iran. Goudarzi and Mostafaeipour [21] investigated a passive system as a renewable configuration for buildings which was economically feasible, and could save considerable amount of investments for the households.

To sum up, from a brief review of the literature, it is evident that researchers have had diverse viewpoints toward optimizing the net present cost of the HRESs. Most common financial indicators which are typically included in the analysis process are the LCOE, EAC, and the NPV. Furthermore, it is worth pointing out that of all the objective functions, selecting an efficient configuration of the HRESs, estimating the minimum number of storage days, minimizing the life cycle costs, and reducing the carbon dioxide emissions have been cited as the most frequent optimization goals. Additionally, tools such as the Fortran programming, HOMER, and linear programming have also been frequently used to perform optimization analysis of these systems.

1.2 Research frame-work

To be able to adequately perform an evaluation of the literature review papers with acceptable accuracy, different parameters should be taken into consideration to conduct an inclusive review which covers a wide variety of objective functions and optimization methods. For this specific purpose, prior to an investigation of the literature review, the current research has aimed to address the following questions: On what basis has the research data been collected? What is the priority by which research papers have been classified in the analysis? How frequently are the utilized optimization techniques in the selected studies employed to perform a precise review of the data? Which research paper has been able to demonstrate the optimization of the HRESs by covering more relative objective functions? Which energy sources are considered as the most important and frequent sources in the optimization and the design process? And during the analysis of the classifications drivers, which design method is frequently used to evaluate the design process of the HRESs?

In this study, a large numbers of the research papers were extracted on a random basis from a variety of authentic sources. The priority was given to those published papers with higher impact factor/ranking journals. From a general observation, it became evident that the application of the heuristic-based algorithms was much more significant compared with other optimization methods.

Prior to an in-depth analysis in the current research, an analysis was also performed to investigate the collection method of the papers in the design process. This issue is particularly important owing to the fact that each method is limited on what it can measure adequately. By proposing multiple methodologies, it would be possible to have more complete data on the phenomenon of interest and a more comprehensive understanding.

In summary, the following points and assumptions were considered during the current analysis: ① The priority of the research subject and its relevance to the optimization of the HRESs; ② The year of evaluation is also important, since it outlines that whether a method has become outdated or not; ③ Furthermore, when it comes to the degree of accuracy, on what occasion a method has been able to precisely perform analysis on the data; and ④ The primary objective of the classification should further be outlined.

In the current research, assessment and evaluation of the HRESs classification drivers have been conducted by categorizing the year of study, grid type, optimization goals, optimization functions, methods and approaches to perform the design and simulations of the HRES, as well as the technology investigated. The search process throughout the literature review was carried out by the google scholar search engine on a random basis. The priority was necessarily given to newer, more relevant and higher citation papers in a selected random group.

Each study was checked based on its relevance with the current state-of-art concerning the HRESs. The attention was more paid to the optimization goals and the algorithms which were used to perform the reliability analysis of the HRESs. Optimization problems in the HRESs were more related to the factors which directly or indirectly affected the general system's reliability and their net present cost as well.

In Table 3, each source type is categorized into different sections in terms of the publication type, the frequency of the journals utilized, and the impact factor (IF) of the journal. Furthermore, in Fig. 1, the contribution of each journal in development of innovative ideas for the design of the HRESs is shown as a pie-chart diagram. To demonstrate the importance or rank of the journals investigated during the evaluation process, the impact factor for each of the journals was taken into consideration as a fundamental measure. It was concluded that, almost 90% of the journal sources in this review have an IF upper than three. Only 4 research sources lacked the IFs, and these belong to the group of conference papers, which were analyzed in the current group of the literature review.

In addition, it is worthwhile pointing out that, as a way to perform a precise citation analysis, classifying the journal types plays a paramount role in analyzing the scientific and technical issues concerned with the design of the HRESs. As demonstrated in Table 3, the current review has concluded that of all journals studied, "*Renewable Energy*," "*Applied Energy*," "*Renewable and Sustainable Energy Reviews*" have the most contributions, the publications with the number of research items being 20, 14, and 12 respectively.

Furthermore, in view of the above literature review, it can also be concluded that many previous research works have investigated different aspects of hybrid renewable energy systems. However, evidently, there has not been a latest research outlining the important classification drivers, which affect the design and reliability of the HRESs from technical, economics, and environmental viewpoints. Therefore, the current research, from a comprehensive perspective, and different from the previously published papers in the field, aims to conduct an inclusive review of the common classification drivers through covering a wide range of the optimization models, algorithms, and technology investigated. For this purpose, a broad range of research papers outlined in the literature review commencing from 2010 up to 2017 have been extracted, and analyzed. The factors studied include the classification drivers for the optimization goals, optimization methods, the commonly, or rarely utilized algorithms, the technical parameters of the design process, such as load demand parameters, energy production factors, level of autonomy, power loss, diesel fuel consumption ratio (in the

Table 3 Categorization of the extracted research papers in terms of the source type

Source type		Frequency of the journals													Impact factor (IF) categorization of the journals (based on 2017 IFs)				
		Top-ranked energy journals												Other sources					
Journal-cases	Con-fer-ence-cases	AE	E	SE	RE	ECM	IEEE-TSE	EPSR	IJEP&-S	IJHE	SEC	JCP	RSER		With no IF	IF ⩽ 1	1 < IF ⩽ 2	2 < IF ⩽ 3	3 < IF
93	5	14	9	9	20	7	2	1	2	7	2	2	12	11	11	0	2	3	82

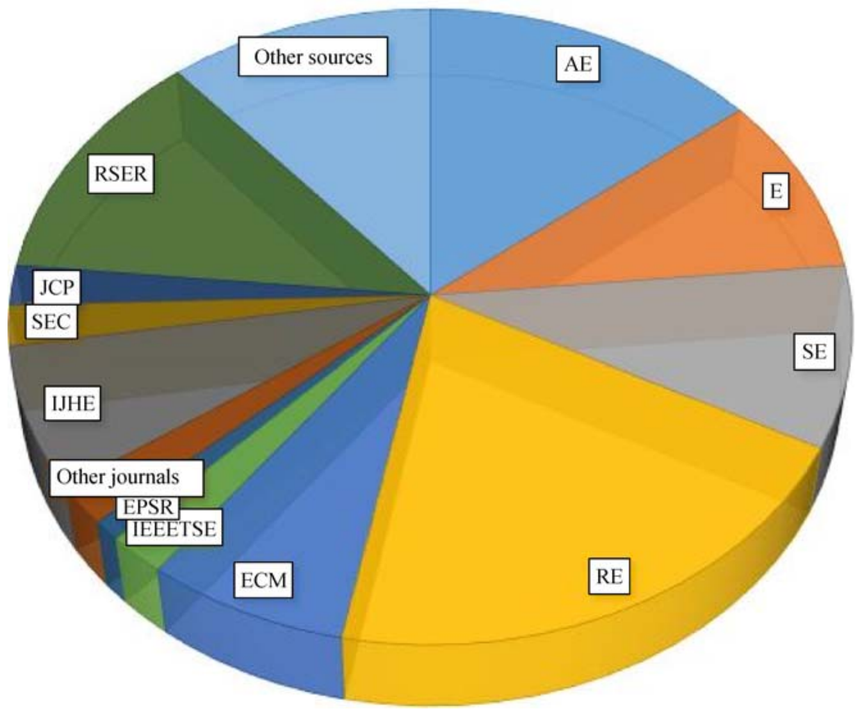

Fig. 1 The contribution of each scientific journal in the advancements of the design and optimization of the HRESs based on current survey report from 2010 till 2017

case that the diesel generator is used), grid parameters (in the case that the system is connected to the grid), such as grid generation point, optimization methods such as heuristics, and meta-heuristics, and newly established mathematical methods, which have not been deeply evaluated yet. Performing an in-depth analysis of the configurations of the HRESs is also another important point, which is exclusively discussed in this research.

2 Analysis of classification drivers

In this section, a comprehensive analysis of the design variables which affect the reliability and cost of the HRESs has been performed. The details of the current analysis are listed in Table 4. This analysis covers a wide range of the research works in the field of HRESs carried out from 2010 up to 2017, taking into account different design variables. A brief glimpse of the table has concluded that:

The load demand, energy production, environmental emission, and the cost are the most important and frequent optimization objectives functions.

Of the heuristic-based design methods, the genetic algorithm (GA), and the particle swarm optimization (PSO), are the most common ones. Linear models are also frequently considered as an effective approach to design and optimize the hybrid power systems lately. Of the tools, the HOMER is the most frequent optimization tool for designing the configuration of the HRESs and estimating the net present cost of the system.

The number of the off-grid hybrid HRESs in comparison with the on-grid ones is more significant.

Evidently, there has been a significant interest in the development and the design of those of the HRESs, which incorporate the WT, PV, inverter and battery-bank inside their configuration. However, there have also been a few

Table 4 A comprehensive review of the classifications drivers for the design of the HRESs

Reference No.	Year	Optimization goals										Methods and approaches to solve the problem									Grid type		Investigated technology						
				Other technical parameters								Heuristic-based methods					Other optimization tools and methods						Energy Sources						Storage
		Load demand parameters	Energy prodction scenarios	Autonomy	Power loss	Diesel fuel consumption	Sizing	Grid parameters	Battery's cycle	Environmental emission	Cost	GA	ACO	PSO	Simulated Annealing	Other heuristic methods	MPC	Mathematical modellings	Mixed Integer Linear Programming	HOMER	On-grid	Off-grid	Wind	Solar	Hydro	Biomass	Fuel cell	Diesel	Battery
22	2010	X	X	X			X				X				X							X	X	X					X
23	2010	X	X								X								X	X		X	X	X	X	X			X
24	2010	X								X	X	X										X	X	X					X
25	2010		X				X			X	X									X		X	X	X				X	X
26	2010	X	X			X				X	X									X		X		X				X	X
27	2010									X	X								X		X			X			X		
28	2010										X				X							X	X	X				X	X
29	2011								X									X				X	X	X			X		X
30	2011						X		X		X							X				X	X	X				X	
31	2011		X				X				X									X	X	X	X	X					X
32	2011		X			X					X								X			X		X	X			X	X
33	2011		X				X				X							X				X	X	X					X
34	2011		X								X							X				X	X	X					X
35	2011	X	X	X						X	X	X				X		X				X	X	X					X
36	2011									X	X					X		X				X	X	X					X
37	2011						X				X					X						X	X		X		X		
38	2012		X							X	X						X				X	X	X	X		X			
39	2012		X				X			X	X									X	X	X	X	X	X			X	
40	2012						X				X							X					X	X					X
41	2012		X								X									X		X		X				X	X
42	2012		X				X				X									X		X	X	X	X	X			X
43	2012						X				X									X		X	X	X				X	
44	2012						X				X	X									X	X	X	X	X				X
45	2012		X				X				X									X		X	X	X					
46	2012				X					X	X	X		X							X		X						
47	2013	X	X			X					X							X				X							X
48	2013						X				X		X									X	X	X	X				X

(*Continued*)

Reference No.	Year	Optimization goals								Methods and approaches to solve the problem										Grid type		Investigated technology					
		Load demand paramters	Energy prodction scenarios	Other technical parameters				Environmental emission	Cost	Heuristic-based methods					Simulation and sampling techniques	Other optimization tools and methods				On-grid	Off-grid	Energy Sources					Storage
				Autonomy	Power loss	Sizing	Battery's cycle			Iterative optimization	GA	PSO	Simulated Annealing	Other heuristic methods	Monte Carlo simulation	MPC	Mathematical modellings	Mixed Integer Linear Programming	HOMER			Wind	Solar	Hydro	Fuel cell	Diesel	Battery
49	2013		X						X			X									X	X					X
50	2013	X				X			X					X							X		X		X		X
51	2013					X			X				X								X	X	X				X
52	2013					X			X								X					X	X			X	X
53	2014					X											X				X	X		X			X
54	2014		X			X			X								X				X	X	X				
55	2014	X	X			X			X										X			X	X				X
56	2014	X				X			X										X		X	X	X	X		X	X
57	2014					X			X								X		X		X	X	X			X	X
58	2014								X								X				X	X	X				X
59	2014		X			X			X										X		X	X	X			X	X
60	2014		X		X		X									X	X				X	X	X			X	X
61	2014	X		X		X		X	X		X										X	X					X
62	2014					X			X					X							X	X	X		X		X
63	2014	X							X					X							X	X	X		X	X	X
64	2014					X			X						X		X					X	X				
65	2015		X			X			X										X		X	X					X
66	2015	X	X						X						X							X					X
67	2015	X						X	X										X		X	X					X
68	2015		X			X			X									X			X	X	X			X	X
69	2015	X							X										X		X	X					X
70	2015	X	X			X			X	X						X					X	X	X			X	X
71	2015	X				X	X		X		X											X	X				X

(*Continued*)

Reference No.	Year	Optimization goals								Methods and approaches to solve the problem										Grid type		Investigated technology						
										Heuristic-based methods						Simulation and sampling techniques	Other optimization tools and methods					Energy Sources						Storage
		Load demand paramters	Energy prodction scenarios	Power loss	Diesel fuel consumption	Sizing	Battery's cycle	Environmental emission	Cost	Iterative optimization	GA	ACO	PSO	Fuzzy logic	Simulated Annealing	HSS	Mathematical modellings	Mixed Integer Linear Programming	HOMER	On-grid	Off-grid	Wind	Solar	Hydro	Biomass	Fuel cell	Diesel	Battery
72	2015		X						X		X		X						X		X		X	X	X		X	X
73	2015		X			X			X	X				X							X	X	X					X
74	2015					X			X	X	X		X							X		X	X					
75	2015	X	X					X	X	X			X				X			X		X	X		X			
76	2015		X										X							X		X	X					
77	2015					X			X			X						X		X		X	X					X
78	2016	X						X	X						X			X			X	X				X		X
79	2016	X						X	X								X				X	X						X
80	2016	X	X			X			X				X								X	X	X					X
81	2016		X					X	X								X				X	X						X
82	2016	X	X			X			X					X								X	X					X
83	2016	X				X							X								X	X	X				X	X
84	2016	X							X				X	X						X		X	X			X		X
85	2016					X			X										X		X	X	X				X	X
86	2017	X		X					X		X		X								X	X	X				X	X
87	2017						X		X								X	X			X		X				X	X
88	2017		X						X							X					X	X	X				X	X
89	2017				X														X			X	X				X	
90	2017	X				X			X										X		X	X	X			X		X
91	2017	X							X								X			X		X	X	X		X		X
92	2017					X	X										X				X		X			X	X	X
93	2017	X					X										X			X			X					X

studies, investigating the optimization of the HRESs, which includes more power generating sources, such as a PV/wind/hydrogen/DG/battery system.

Furthermore, as a result of the detailed analysis of the classification drivers shown in the Table 4, a spider diagram outlining the relations between each of the design variable and the objective function of the HRESs is depicted in Fig. 2.

To design a table in a smaller-scale group on the one hand, and on the other hand, to lower the length of the table so that it would become a more appropriate resolution, two primary considerations are put into effect during filling out the table: ① Parameters, such as optimization goals, algorithms, and the other design factors which have very few ticks are removed from the table of classifications; however, they are analyzed during the categorization process. These parameters are day-ahead, SFL (shuffled frog leaping), P-ICA (parallel imperialist competitive algorithm), MPC (model predictive algorithm), GRG (generalized reduced gradient), VSI (voltage stability index), cuckoo search method, BBO (biogeography-based optimization), LST (load shifting technique), smart grid theory (SGT), DIRECT method, PPOA (power pinch optimization analysis), MCDM (multi-criteria decision making), SEMA (smart energy management algorithm), B&B (branch and bound) algorithm, Pareto algorithm, MOABC (multi-objective artificial bee colony), ANN-based methods, trnsys model, BGED (break-grid extension distance), big bang-big crunch (BBC) algorithm, perturb and observe algorithm (P&O). ② To investigate a wider spectrum of the research papers which deal with the design of the HRESs, more publications than the range considered in the table are also included during the analysis process to cover more optimization goals and methods.

An analysis of each of the design variable and objective function as well as the number of their frequencies, which have been used in the table of classification drivers are outlined in subsequent sections.

2.1 Categorizing optimization goals

The classification and contribution of the most prevalent optimization goals has been performed. Clearly, as shown in Fig. 3, the frequency of optimization goals in the design process highlights considerable variations in the contributions of the optimization functions. Evidently, the cost factor has been the most prevalent design variable with its allocation being 84. Sizing and configuration has also contributed to a majority of the performed research works in the literature review. The other common optimization goals are load demand parameters, energy production, and environmental emissions, with contributions of 31, 32, and 17 respectively. The less commonly used optimization goals are IGP, GGP, BGED, VSI, and charge scheduling.

2.1.1 Factors affecting load demand

Among 98 studies performed in the current survey concerning the design and optimization of the HRESs, load demand has been cited 30 times. The most important load factors which have been considered to affect the reliability of the system are the LLP and the LPSP which have a significant impact on the performance and reliability of the system.

(1) Loss of load probability (LLP)

The value of the LLP can be determined using [22]

$$\mathrm{LLP} = \frac{\sum_{h=1}^{h=8760} \text{energy deficit } (h)}{\sum_{h=1}^{h=8760} \text{load demand } (h)}, \tag{1}$$

where the energy deficit (h) is the amount of required energy provided by the load at a certain hour, which cannot

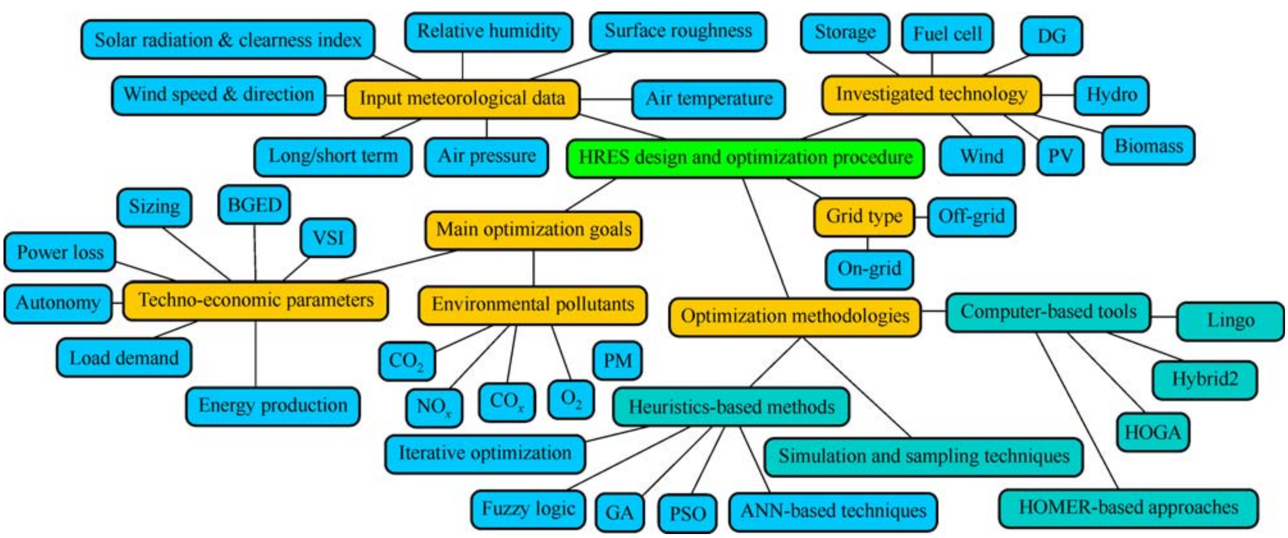

Fig. 2 The optimization and design process of the HRES by considering different classification drivers

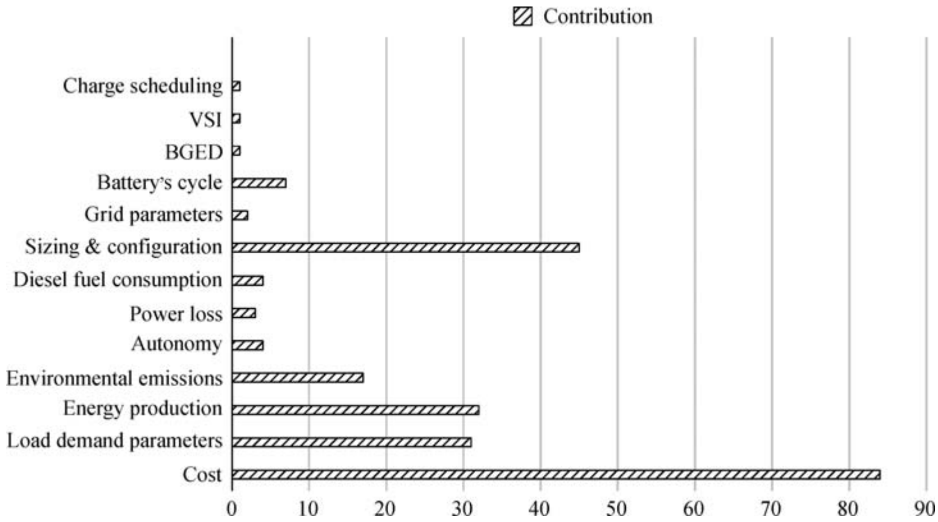

Fig. 3 Frequency of the common optimization goals

be covered by the various generation or storage sources. This parameter can be estimated using [22]

$$h = \text{load demand } (h) - [E_{\text{pv}}(h) + E_{\text{MTE}}(h) + E_{\text{MTH}}(h) E_{\text{B}}(h-1)]. \quad (2)$$

Another way of expressing the LLP is considered to be

$$\text{LLP} = \frac{\sum_{j=0}^{n} s_j}{\sum_{j=0}^{n} c_j}. \quad (3)$$

(2) Loss of power supply probability (LPSP)

The LPSP is defined as the ratio of all energy deficits to the total load demand during the period considered. A LPSP of zero is indicative of the fact that the load will always be satisfied, and the LPSP of one shows that the load will never be satisfied. Rajkumar et al. [35] has defined the LPSP based on the interactions which arise from the relationship among the load demand parameter, the energy production generated by the renewable source and battery's state of charge. As a result, the following relation has been established:

$$\text{LPSP} = \frac{\sum (P_{\text{load}} - P_{\text{pv}} - P_{\text{wind}} + P_{\text{SOC,min}})}{\sum P_{\text{load}}}, \quad (4)$$

where P_{load} is the load demand of the system, P_{PV} is the power production from the PV array, P_{wind} is the power production from the WT, $P_{\text{SOC,min}}$ is the minimum state of charge of battery. It is noted that the LPSP defined here does not include the energy deficit owing to the component breakdown or maintenance down-time. It is merely in relation with the size or capacity of the energy storage as well as the load demand [35].

(3) Load shifting technique (LST)

In the current survey analysis, the LST (load shifting technique) is considered one time as an optimization goal. As a matter of fact, the LST refers to a load parameter which falls into two classifications, the low priority load (LPL) and the high priority load (HPL). HPL is applied in an occasion where the energy production of the HRES is restricted to a constant level, therefore requiring any available sources (renewable sources, storage, or traditional sources of power) to supply the necessary electricity demand. Nevertheless, the LPL can be supplied when the production from renewable sources of power is available and it can then be fed from the surplus generation time of the HRESs. On the occasion that the energy source produced by the renewable energy sources exceeds the power required for the HPL, the surplus energy will be stored in the batteries even up to its maximum level. The excess power will be considered for utilization to feed the LPL. The excess power above the LPL requirements will be considered for utilization to feed the dummy load, which is a device, for simulating the electrical load. The unmet LPL will be shifted to the time of surplus generation. Provided that the power required for the HPL is greater than the power generated by the renewable sources, an energy storage system could then be used to ensure the required demand for the HPL until the required energy decreases to its least level. The unmet LPL will be shifted to the time of surplus generation [84,94,95].

2.1.2 Energy production scenarios

Parameters related to energy production have been considered in 32 research studies. As a matter of fact, different scenarios have been considered to evaluate energy production in different ways. Samples of such indexes which have been included in the current survey are energy index ratio (EIR), expected energy not supplied (EENS), wasted renewable energy (WRE), excess electricity fraction (EEF), and deficiency of the power supply probability (DPSP).

(1) Energy index ratio

Kanase-Patil et al. [23] defined the energy index ratio (EIR) as

$$\mathrm{EIR} = 1 - \frac{\mathrm{EENS}}{E_0}, \tag{5}$$

where EENS is the expected energy which is not supplied (kWh) and E_0 is the total energy demand of the system (kWh). The EENS is defined based on

$$\mathrm{EENS} = L \times \frac{D}{3600}, \tag{6}$$

where L is average annual power load (kW); D (seconds) is the duration of a load, which is unavailable. The EIR as well as the EENS is considered only in one of the studies out of the 98 researches conducted. The EIR has been used to evaluate the reliability of the HRESs designed to aid the load demand for supplying the required electricity. It has been suggested that in order to have the best configuration of the HRESs, the system has to have an EIR of above 0.9, highlighting the fact that the system should be 90% reliable in its performance [23].

(2) Wasted renewable energy (WRE)

The WRE is considered as a design parameter in one of the studies performed in 2013 and it is defined based on [84]

$$\mathrm{WRE} = \sum\nolimits_{t=1}^{t=8760} P_{\mathrm{w}}(t) + P_{\mathrm{spv}}(t) - P_{\mathrm{eld}}(t) \ \ \forall t,$$

$$s.t. \quad P_{\mathrm{w}}(t) + P_{\mathrm{spv}}(t) - P_{\mathrm{eld}}(t) \ \text{ and}$$

$$\mathrm{SOC}(t) = \mathrm{SOC}_{\max}(t), \tag{7}$$

where $P_{\mathrm{w}}(t)$ is the electric power from the wind turbine, $P_{\mathrm{spv}}(t)$ is considered as the solar PV output, SOC(t) is the state of charge of the battery, $P_{\mathrm{eld}}(t)$ is electricity load demand, and $\mathrm{SOC}_{\max}(t)$ is the maximum state of charge of the battery.

(3) Excess electricity fraction (EEF)

The EEF is defined in the following form (as shown in Eq. (8)) and has been considered in the two research studies conducted lately (one study in 2011 [35] and the other in 2014 [61]).

$$\mathrm{EEF} = \frac{\sum (P_{\mathrm{load}} - P_{\mathrm{PV}} - P_{\mathrm{wind}})}{P_{\mathrm{renewable}}}, \tag{8}$$

where P_{load} is the load demand of the HRES, P_{PV} is the energy production from the PV array, P_{wind} is the power from the wind turbine, and $P_{\mathrm{renewable}}$ is the power production from the renewable energy.

(4) Deficiency of power supply probability (DPSP)

DPSP is a design variable for expressing the reliability of a HRES proposed and is defined as the probability that an insufficient power supply results when the other components of the HRES (for instance, PV array, WT, and battery) are not capable of satisfying the load demand. The DPSP is considered to be a technical criterion to perform sizing and evaluation of an HRES, which employs battery-pack and therefore, by using this parameter as the objective function in the optimization process, an HRES configuration with a high efficiency and reliability can be achieved.

The DPSP is defined according to [33]

$$\mathrm{DPSP}(t) = \sum\nolimits_{t=1}^{T} \mathrm{DPS}(t) / \sum\nolimits_{t=1}^{T} E_{\mathrm{L}}(t), \tag{9}$$

$$\mathrm{DPS}(t) = E_1(t) - [E_{\mathrm{gen}}(t) + \mathrm{SOC}(t-1) - \mathrm{SOC}_{\min}]\mu_{\mathrm{inv}}, \tag{10}$$

where DPSP(t) is the deficiency of power supply probability at time t; DPS(t) is the deficiency power supply (DPS) at hour t, which is related to the control system, which disconnects the load and the deficit of the HRES; $E_{\mathrm{gen}}(t)$ is the energy production of the HRES at time t; μ_{inv} is the inverter efficiency of the HRES; and SOC(t) is the state of charge of the battery of the HRES.

The DPSP, for a considered period T (for instance it can be assumed to be one year), and is generally defined as the ratio of all the (DPS (t)) values for that period to the sum of the load demand. A DPSP of one refers to the fact that the load will never be satisfied and the DPSP of zero indicates that the load will invariably be met.

(5) Level of autonomy (LA)

In this review, the LA is considered four times as an objective function. This parameter is defined as one minus the ratio of the total number of hours, in which the loss-of-load occurs in a hybrid power system (D_{lol}) to the total hours of operation (D_{tot}), and is given by [11]

$$1 - \frac{D_{\mathrm{lol}}}{D_{\mathrm{tot}}}. \tag{11}$$

2.1.3 Factors affecting the system's grid during optimization process

Parameters related to the system's grid during the optimization process, are GGP (grid generation points) and IGP (independent generation points), which have been considered only in one study in 2013 during the current survey analysis. As a matter of fact, the GGP is considered as a situation where the energy is produced and distributed to other demand points through a distribution network (radial micro-grid) while the IGP is defined as the points producing energy just for their own consumption and not connected to any micro grid [22].

2.1.4 Reduction of environmental emissions

Decreasing the concentration of the environmental pollutants produced by those of HRESs, which also employ the DG in their configuration, has been considered as one of the primary objective functions to adequately design environmentally-friendly HRESs with the least release of the greenhouse gasses to the atmosphere. The environmental emission factors which are considered in the design procedure in the literature review are as follows:

(1) Global warming potential

Global warming potential (GWP) is defined as the relative estimation methodology of how much heat a greenhouse gas is able to trap in the atmosphere. As a matter of fact, it performs estimations by comparing the amount of heat which is inside a certain mass of the gas in question and the amount of heat trapped by a similar mass of the greenhouse gas. The GWP is typically measured over a specific time interval, commonly 20, 100, or 500 years outlining the emissions of the carbon dioxide, whose GWP is standardized to a unit value.

The GWP parameter is contingent upon the absorption of infrared radiation by a given species, the spectral location of its absorbing wavelengths, and the atmospheric lifetime of the species.

$$\mathrm{GWP}(x)=\frac{\int_0^{\mathrm{TH}} a_x\cdot[x(t)]\mathrm{d}t}{\int_0^{\mathrm{TH}} a_r\cdot[r(t)]\mathrm{d}t}, \tag{12}$$

where TH is the time horizon over which the calculation is considered, a_x is the radiative efficiency due to a unit increase in atmospheric abundance of a substance (i.e., $\mathrm{W\cdot m^{-2}\cdot kg^{-1}}$), and $[x(t)]$ is the time-dependent decay in abundance of the substance following an instantaneous release of it at time t equals zero.

(2) Equivalent CO_2 LCE

As a matter of principle, it is important to bear in mind that, analyzing the life-cycle emissions takes into account estimating the global-warming potential of the energy sources through calculating the life-cycle of each energy source. Such estimations are usually presented in units of "global warming potential per unit of electrical energy generated by that source." This equivalent CO_2 LCE parameter employs the GWP unit, the carbon dioxide equivalent (CO_2 emissions), the unit of electrical energy, and the kilowatt hour (kWh). The purpose of such evaluations is to cover the full life of the power source, from material and fuel mining through the construction to operation and waste management.

One aspect of the life cycle emissions analysis is the equivalent carbon dioxide life cycle emissions CO_2 LCE (gCO_2/kWh) which is defined as the equivalent carbon dioxide emissions usually produced by the DG or any power-generating equipment, which releases carbon dioxide emissions into the atmosphere. This parameter is taken into account to manufacture, transport, and recycle the components of the system (i.e., PV panels, structures, WT, diesel or gasoline generator, batteries, inverter, charge regulator, and rectifier). It also includes the emissions from the fuel combustion of the diesel or gasoline generator, fuel extraction and refining, and fuel transport.

In off-grid HRESs, the equivalent CO_2 LCE is considered to be the emissions per kilowatt-hour utilized by the electrical load. In a research conducted by Dufo-López et al. [36] in 2011, optimization of this parameter was conducted by employing the HOGA optimization tool.

(3) DG environmental pollutants

The DGs generally produce gas pollutants into the atmosphere. The primary polluting gases released by the DG are CO_2, NO_x, SO_2, CO, and PM_{10}. Optimization of the environmental pollutants could then be performed specifically for every single contaminant such as the carbon dioxide, unburned HC particulate matters, NO_x, SO_2, and other environmental emissions by taking into account an upper bound limit for each of the aforementioned pollutants. On this account, HOMER, has a powerful option method, which specifically performs emissions control and restrictions on each of the pollutants released by the HRESs integrated with the DG by considering a maximum limit control on these emissions.

In a research conducted in 2012, Nasiraghdam and Jadid [46] employed a calculation methodology, for estimating the total annual emissions produced with the support of a grid-tied hybrid power system as

$$\begin{aligned}\mathrm{Min}\ f_4(x) &= \sum\nolimits_{i=1}^{N.\mathrm{hybd}}\sum\nolimits_{j\in\mathrm{Tech}} P_{i,j}\times \mathrm{ER}_j\times \mathrm{CF}_j\\ &\quad\times 8760+P_{\mathrm{sub}}\times \mathrm{LF}\times \mathrm{ER}_{\mathrm{grid}}\times 8760,\end{aligned} \tag{13}$$

where ER_j and the $\mathrm{ER}_{\mathrm{grid}}$ are the emission rates of the jth technology of the DG and the grid, respectively; P_{sub} is the purchased power from the main substation; LF is defined as the load factor; 8760 is the total number of hours that the hybrid system is operating throughout the year; and $P_{i,j}$ is the active power generated by the ith hybrid system that has jth technology of the DG, PV, WT or FC.

Among all pollutions considered, carbon dioxide is always seen as the primary source of the greenhouse effect. In a latest research in 2015 conducted by Shi et al. [69], the produced DG carbon dioxide emissions were estimated by

$$F_{\mathrm{CO_2}}=\sum\nolimits_{t=1}^{T} F_{\mathrm{cons}}(t)E_f, \tag{14}$$

where E_f is emission factor, a parameter depending on the characteristic of the DG as well as the fuel, and its value usually lies in the range of 2.4 to 2.8 kg/L; and F_{cons} is considered as the fuel consumption of the DG [69].

2.1.5 Voltage stability index (VSI)

VSI is a design parameter in most of the HRESs, which should be enhanced. For detecting a bus of radial distribution systems that is most sensitive to voltage collapse, the VSI has been introduced for each bus. VSI is a number between zero and one, which is expressed as unity for no load, and zero at the point of voltage collapse. It is, therefore, desirable that the VSI parameter be close to unity for each bus as much as possible. In detail, the VSI index is elaborated according to a formula outlined in Ref. [46].

2.1.6 Breakeven grid extension distance (BGED)

The maximum distance from the grid, which makes the net present cost of extending the grid equal to the net present cost of stand-alone system is called breakeven grid extension distance and is estimated based on [96]

$$D_{\text{grid}} = \frac{C_{\text{NPC}}\text{CRE}(i,R_{\text{proj}}) - C_{\text{power}}E_{\text{demand}}}{C_{\text{cap}}\text{CRE}(i,R_{\text{proj}}) + C_{\text{om}}}, \tag{15}$$

where C_{NPC} is the total net present cost of the stand-alone power system ($), CRF is capital recovery factor, i is interest rate (%), R_{proj} is project lifetime (a), E_{demand} is total annual electricity demand (kWh/a), C_{power} is the cost of power from the grid ($/kWh), C_{cap} is the capital cost of grid extension ($/km), and C_{om} is the operation and maintenance (O&M) cost of grid extension ($\$\cdot(\text{a}\cdot\text{km})^{-1}$).

Based on the current review, BGED is only considered one time as an optimization goal in a study performed by Hafez and Bhattacharya [41]. In the aforementioned study, the effect of the distance from grid and the optimal break-even distance was addressed.

2.1.7 Sizing and configuration methods

The sizing and configuration of the HRESs have always been considered as the primary stage of the design and optimization process. A research conducted in 2012 [97] categorized the sizing and configuration methods into four main classifications: probabilistic, analytical, iterative and the hybrid model. By investigating more about the details of each of these classifications, Table 5, which demonstrates an inclusive review regarding the classification of the sizing methods from 2003 until 2010 is presented to analyze the latest optimized indicators, and the design constraints, which affect the sizing optimization of the designed HRESs. On this analysis, grid type as well as the investigated technology has also been taken into consideration.

Brief description of each method of the sizing based on Table 5 is detailed as follows:

(1) Probabilistic methods

Probabilistic methods are considered as the easiest ways of configuring the size of the HRESs. However, the results obtained by using this method are not always considered as the most appropriate ones to estimate the best solution or configuration of the HRESs. Generally, one or two system performance indicators are enhanced to achieve the optimal result in order to perform the sizing of each component.

As an example demonstrated in Table 5, a study performed in 2003 employed a novel probabilistic approach according to a convolution technique by using the probability density function (PDF), with the aim of specifying the probability of a random variable falling within a particular range of values in order to evaluate the long-term performance of hybrid PV-Wind systems and then to perform the sizing procedure [98].

(2) Analytical methods

Analytical methods utilize the computational models, which describe the size of the hybrid system as a function of its techno-economic viability. Using such methods, the performance of the system can be evaluated for each of the HRES components. The analytical method has the merit of letting the designer know how to establish simulations of the system's performance and efficiency of the several HRES configurations. The drawback of this method is that it requires a longer span of time for the weather data in order to perform the simulation and optimization process. On this account, recently, there have been many computer tools to carry out the performance of the HRESs, which aid the designer to perform analysis for the integration of different renewable sources. Example of these tools, are HOMER, Hybrid2, and HOGA [97].

(3) Iterative models

Iterative methods employ the recursive process, with the aim of ceasing the optimization process in an occasion that the most efficient configuration is achieved on the basis of the design characteristics. For instance, in a study conducted in 2007 [4], the iterative method was used to achieve the optimal configuration of the HRESs for a rural village by decreasing the LCC to a minimum level and maximizing the reliability of the systems. For this purpose, a numerical algorithm based on the Quasi-Newton method (which are a series of methodologies employed to either find zeroes or local maximum and minimum of functions was used to solve the optimization problem). Generally, the procedure for performing the sizing methods using the iterative optimization would fall into four main classifications: Selecting the models and the numbers of each of the HRES components, which are commercially available; considering a constant number for each of the HRES components, and then increasing the number of the other components to achieve an optimal energy balance; performing the second stage again for the variety of WTs or PV arrays to reach all available configurations; and calculating the necessary storage capacity by summing up all energy variations between the HRES production and the storage [97].

(4) Hybrid models

It is imperative to bear in mind that most of the optimization problems have a multidimensional nature.

Table 5 Classification of the sizing methods, which are used in the design and optimization of the HRESs

Reference No.	Year	Sizing classifications				Optimized indicators															Design constraints											Grid type		Investigated technology			
		Probabalistic	Analytical	Hybrid	Iterative	Cost drivers							Energy parameters			Load indicators		PGA	UAC	Battery's SOC	LPSP	LA	FLMPVS	WLR	GDB	Pc	RA	LCE	UAC	Cleanness index	Laod demand	On-grid	Off-grid	Wind	PV	Hydro	Battery
						LCC	COE	NPC	NPV	IRR	PVEC	TMC	EENS	EIR	EE	LLP	LPSP																				
[98]	2003	X					X			X			X	X			X			X	X												X	X	X		X
[99]	2003	X					X						X									X											X	X	X		X
[100]	2011	X								X	X		X	X									X										X	X	X		X
[101]	2005			X												X													X	X			X		X		X
[102]	2005			X														X	X		X												X		X		X
[103]	2006				X			X																							X		X	X	X		
[04]	2007				X	X																					X						X	X	X	X	
[104]	2007				X												X											X					X	X	X		
[105]	2007			X														X	X		X												X		X		X
[106]	2009		X								X												X									X			X		
[107]	2009		X												X									X	X	X									X		
[108]	2010		X									X																					X	X	X		

Therefore, in order to sufficiently address an optimization problem, a suitable method of optimizing is the one which is able to solve a multi-objective problem on the basis of the heuristic methods such as the GA, PSO, neural network, and the Tabu search. Additionally, the hybrid methods have the advantage of combining two or even three optimization methods together to give the best and the most effective results [97].

2.1.8 Classification of sizing based on availability of weather data

Bajpal and Dash [109] have considered another viewpoint to classify the sizing and configuration. On this basis, two main categories are taken into account: conventional techniques which require the weather data from the meteorological sites for a specific location and artificial intelligence (AI) techniques which are performed in an occasion when the weather data are not available. Examples of the AI models include artificial neural network (ANN), fuzzy logic, genetic algorithm, wavelet transforms, and hybrid models. Conventional techniques are based on the energy balance and the reliability of energy supply.

Another research conducted in 2015 by Wang et al. [72] has considered the energy flow optimization method in an occasion that weather data are achievable for a specific location. On this basis, the energy flows during a typical day with the averaged weather data are considered for the sizing methods. Using this method, the average weather data for a region are extracted by sampling the seasonal weather data. Afterwards, such data are compared with the solar radiation, wind speed, and temperature values at the same hour of different days to estimate their mean values. The corresponding solar and wind energy production can be achieved as the upper limits when performing the power dispatch for a study.

2.2 Optimization methods and tools

Over the past decade, there has been a significant growth and interest in development of tools and methods which are used to perform the optimization of the performance and efficiency of the HRESs by employing the latest computational models (i.e., commercial software tools and/or numerical approximations of system components). Such tools which are developed to evaluate the performance of the HRESs aim to aid the designer to analyze the integration of multiple renewable sources. Optimization methods considered in the current analysis fall into three classifications, which are the heuristic-based methods, the simulation and sampling techniques, and other optimization tools and soft-wares.

Figure 4 demonstrates variations of the common optimization methods and algorithms which have been used for the design of the HRESs. Evidently, the HOMER is the most common tool with its contribution being 25. Other commonly used methods during the design and optimization of the HRESs are GA, PSO, MILP, SA, and iterative optimization.

2.2.1 Common heuristic-based models

Heuristic optimization is one way for the optimization process, which is established by trial and error and its main purpose is to generate adequate solutions and responses to a complex problem in a reasonably practical time. Such methods typically fall into two classifications, heuristic and metaheuristic methods, though their difference is insignificant. Generally, heuristic is defined as “to find” or “to explore by trial and error” [73].

In this review, of all studies performed, the PSO, the GA, and the linear programming have been the most frequent methods.

(1) Genetic algorithm (GA)

GA, an optimization method inspired by natural selection and derived from the biological evolution, aims to solve both constrained and unconstrained optimization problems. The GA repeatedly modifies a population of individual solutions [110]. This method has been used in 12 research studies out of 98 research cases.

(2) Particle swarm optimization (PSO)

PSO, developed in 1995, has many similarities to the GA method. PSO is a population-based stochastic optimization method and it is inspired by the social behavior of bird flocking or fish schooling [111]. The PSO algorithm has been considered for utilization in ten research studies out of 98 research cases.

(3) Linear-based optimization models

The linear programming (LP) is defined as a method for achieving the best outcome, such as maximum profit or the least cost value in a mathematical modeling process, whose requirements are represented with linear relationships. Many LP models can be solved through the Simplex method, which is similar to the Gauss-Jordan algorithm based on the linear algebra. The model can simply explore the global optimum solutions. Nevertheless, every function using this method should be linear, which can occasionally produce unrealistic solutions. The LP method is most commonly utilized to find the upper limit of solutions [112].

In this review, 11 research projects (out of 98 papers) have employed the linear optimization techniques to design and optimize the HRESs.

By way of an example, a research which was performed by Malheiro et al. [70] addressed the optimum sizing and scheduling of an isolated HRES by employing an advanced optimization framework which included a mixed integer linear programming model to analyze the performance of the system over a time horizon of one year,

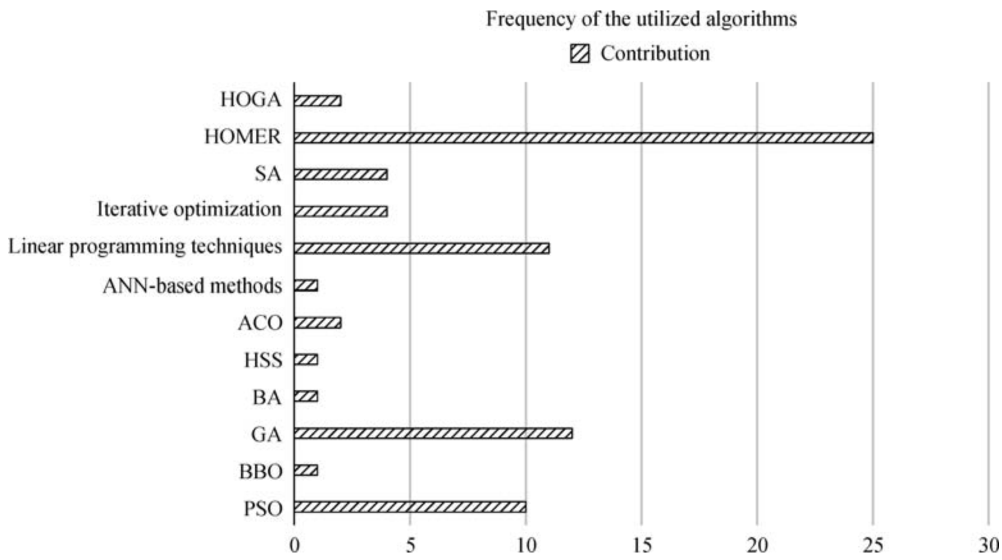

Fig. 4 Contribution of the commonly used algorithms and methods

considering hourly variations in both the availability of the renewable resources and the energy demand as well. The purpose of the study was to design the configuration of the HRESs incorporating the WT, the PV arrays, the battery-bank, and the DG as a back-up system to provide electricity demand for the application considered. The optimal configuration considering the levelized cost of energy (LCOE) over a lifetime of 20 years was performed.

2.2.2 Simulation and sampling techniques

In the current in-depth review, three assessment methods are identified under the group of sampling and simulation techniques, which are Hammersley sequence sampling (HSS), simulated annealing (SA), and the Monte Carlo simulation technique. Out of 98 research studies investigating the configuration of the HRESs, four research papers have implemented the SA method. However, the HSS model as well as the Monte Carlo simulation has only been proposed for the application of the HRESs only once in the current analysis.

The SA method, proposed in 1983, is an intriguing technique for optimizing the functions of different design variables. This heuristic method which also operates as a sampling technique aims to optimize the NP-complete problems for which an exponentially number of steps is required to generate a relatively accurate approach. As a matter of fact, the term “NP” stands for “nondeterministic polynomial time.” The “NP-complete” which is defined as the class of decision problems, contains the hardest problems in NP. This decision problem belongs to both the NP as well as the NP-hard complexity classes. Additionally, the NP-hard is defined as the property of a class of problems, which are informally, “at least as hard as the hardest problems in the NP.” An example of the NP-hard could be observed in decision-making problems. Another example can be observed when finding the least-cost cyclic route through all nodes of a weighted graph, which is commonly known as the traveling salesman problem. However, the example of the NP-complete is observed in the isomorphism problems. Other types of the NPs which are utilized are NP-easy, NP-equivalent, and NP-intermediate.

It is worthy to mention that, in a comprehensive research conducted by Ekren O and Ekren B Y [22], an SA model has been developed to perform optimal sizing of a PV/wind system incorporating an energy storage system. In their study, the objective function was minimization of the total cost of the HRESs. The decision variables were the PV array size, WT rotor swept area, and the battery’s capacity. The optimum results which was achieved by the SA method was then compared with the results of another study which used the response surface methodology (RSM) in its analysis. Consequently, it was suggested that the SA approach employed provides more accurate solutions than the RSM mathematical model. Afterwards, a case study was then taken into account by evaluating the effectiveness of the employed model for a campus area in Turkey.

In a recent research performed in 2017 [88], the Hammersley sequence sampling (HSS) method was employed as a multi-objective optimization framework with the aim at decreasing the cost to the least value, enhancing the energy production, and then inventing an advanced reliability method, to adequately design the sketch of a PV/Wind/FC system, which also incorporates the DG as a back-up source in its configuration. An evaluation of the energy supply reliability outlined a relation among the energy demand and the energy produced by the designed HRES. Furthermore, during connecting the HRES with the electricity grid, the model proposed estimated the dynamic response of each power unit taking into account the WT, the PV array, and the FC in the HRES configuration. In addition, the fluctuation of the electricity produced by each power unit and the overall energy generated by the designed HRES was then analyzed by employing an evolutionary multi-objective optimization model.

Another sampling method which has been identified in the current survey analysis is the Monte Carlo simulation technique which relies on the repeated random sampling to estimate the numerical results. This method was used to investigate the optimum design and scheduling of an HRES under uncertainty conditions [68]. Furthermore, a method was then developed and implemented to investigate the decisions on the equipment installation of the PV/wind/DG/battery HRES. Specifically, the purpose of the model was the detection of the optimum size and configuration of the HRES proposed as well as the energy storage systems in each power station in order to achieve the minimum total cost expected, while satisfying the power demand of each area.

2.2.3 Other optimization tools and methods

According to the analysis performed for each of the classification drivers of the HRESs, it was concluded that the HOMER, the Lingo, and the Matlab Simulink design optimization (MSDO), were the most frequent soft-wares employed in the optimization modeling of the HRESs. Other optimization tools, which have also proved to be useful are model predictive control (MPC), the branch-and-bound (B&B), the generalized reduced gradient (GRG) techniques, and multi criteria decision making.

Furthermore, the smart grid theory, which enables interaction between the generation and load to optimally deliver energy based on the operating conditions, has also been considered in studies lately. Although smart grid solves many of the contemporary problems, it gives rise to new control and optimization problems especially with the growing role of renewable power sources.

Some of the methods utilized also cover a wider variety of processes. For instance, in a study conducted in 2015 by Wang et al. [72], the receding horizon optimization (RHO), which is considered as a classification of MPC has been proposed to minimize a certain cost function over a moving time-horizon to estimate the optimum energy generation of those of power-generating equipment, which are under the group of larger systems. Basically, the MPC method is widely utilized in engineering and design of process systems for industrial applications.

In addition, the current analysis has demonstrated that out of 98 studies, 12 researches are performed with the support of the HOMER tool, two researches perform configuration of the hybrid power systems using the Lingo modeling software, one study deals with the application of the MSDO soft-ware, and another research performs an optimization analysis on the performance efficiency of an HRES by employing the GRG-B&B method.

As it is concluded by the literature review, the HOMER software has considerable merits. On the top priority, it is user-friendly. Second, it is extensively utilized for the techno-economic as well as the environmental emission analysis. The energy sources investigated in the HOMER could cover a wide variety of the natural sources, not just renewable ones, such as the PV, the WT, hydro, biomass, but also the conventional sources of power such as diesel fuel. The software is capable of performing the thermal systems analysis as well.

Optimization and simulation of the HRESs using the iHOGA tool has also been performed in two research cases, one in 2011 [35] and the other in 2014 [63]. The iHOGA is a strong optimization tool, which can aid the achievement of the least-cost design of a system throughout the whole lifetime operation of the HRES. Similar to the HOMER software, the NPC is one of the primary objective functions considered during the analysis. Minimizing carbon dioxide emissions and the unmet load, which refers to the energy, that is not served, should also be taken into account during the optimization process and analysis to provide better insights concerning the optimization of the HRESs. It is noted that both HOMER and iHOGA have been programmed using the C++ programming language.

In some rare occasions, chemical methods such as the pinch analysis method, which are typically utilized to minimize the energy consumption in the chemical processes, and thermodynamic cycles, have also been considered as an optimization method to reduce the net present cost of the hybrid power system to a minimum level.

Some primary software tools which have also been utilized recently to perform analysis on the hybrid renewable energy systems include Rapsim, Trnsys, RETScreen, Insel, PV sol, iGrhyso, SOMES, Solstor, Hysim, Hybsim, IPsys, Hysys, Dymola/Modelica, ARES, Solsim, and the Hybrid designer [113].

It is worth pointing out that there are particular advantages and disadvantages for each of the tools or methods used in the analysis of the HRESs. For instance, the HOMER tool which is a user-friendly and freeware software makes it a simple way to analyze the sizing procedure, with efficient output diagrams, which could then be used and is helpful for a better analysis of the optimization results and outcomes. On the downside, the tool lacks the use of coding analysis and development of different optimization models. Such an issue could possibly lead to inflexibilities in the development of the more comprehensive and advanced hybrid energy models, which could then aid experts and designers to supply more extensive outcomes and results. This situation is also correct for many other tools or software, which are exclusively made for the design of the HRESs, such as, Hybrid2, iHOGA and etc.

The ANNs, which have a performance such as pattern classification methods, are computing systems, inspired by the biological neural networks, which constitute animal brains. Such systems learn to progressively enhance the performance of the model and to perform the tasks by considering examples, generally without task-specific programming. In the ANNs, there are various criteria which are proposed to select the number of hidden neurons. Afterwards, the evolved criterion will lead to design of an intelligent ensemble neural network structure which can then be proposed to predict climatic conditions or other necessary characteristics for any renewable energy applications including the HRESs. The ANNs are increasingly used in various areas thanks to their capability of handling complex systems specificities. Examples of ANNs applications can be observed during the design of the MPPT (maximum power point tracking) controllers of the photovoltaics, as well as wind energy systems [114].

Other primary and common methods which have been extensively used during the design of the HRESs are heuristic-based algorithms such as the GA, PSO, and SA, which have the great advantage of being strong and fast for solving a variety of mathematical problems, which typically have a complicated structure. Their application usually covers a wide range of issues including computer science, chemical science, automated design, control engineering, mechanical engineering to even biology. On the downside, their coding procedure is typically a complicated and time-consuming process to implement and run.

Extensive mathematical modeling methods have been derived from different research papers to perform modeling of the WTs, solar cells, DGs, battery strings, and other primary components of the hybrid power system. The purpose of each model has been to look for an accurate, close mathematical model which represents a powerful methodology to estimate the power generation as well as viability of the hybrid system considered. When an approximate or near closer mathematical model is available, it would be easier to test the system for suitability without spending money prior to the fabrication. From a mathematical modeling viewpoint, the next stage would be the development of the computer simulation models to evaluate the performance of the system for stability and output results under various input conditions. These computer simulations can be used for further analysis or to change various components or to redesign the system for better results before fabricating the final prototype models.

The results of the current review has showed that in 8 research cases, the mathematical modeling techniques with no specific optimization model has been performed to analyze the efficiency and optimization of the HRESs.

For instance, in a research carried out in 2011, an economic approach, according to the concept of the levelised unit electricity cost (LUEC), was adopted to discover the best indicator of the economic profitability of the system. Afterwards, a grid-independent hybrid PV/wind system was simulated by running the program developed to study the relationships between system power reliability and system configurations. The optimal configurations of the hybrid system were determined in terms of different desired system reliability requirements and the LUEC parameter.

With regard to mathematical modeling techniques, in another research conducted in 2017, Bordin et al. [9] investigated the application of the linear programming methodology to perform a comprehensive analysis and review concerning battery degradation for the optimization application of an off-grid power system with solar energy integration. They studied a mathematical formulation for an off-grid hybrid system to optimally manage the battery integration. During the optimization process, the constraints were considered to be the load demand, the DG demand, the minimum production of the system, the maximum DG capacity, the converter efficiency, the renewable source capacity, the initial values of battery variables, the minimum battery charge level, the charge and discharge processes management, and the battery maximum charge level. The final results of this study emphasized the importance of the economic operation of storage capacities, which took into account the relationship between the degradation of a battery and the operating pattern to meet the electricity requirements of an off-grid site.

2.3 Cost drivers

To address the techno-economic viability of a renewable energy project, researchers have had different viewpoints on the analysis of the cost. Based on a review performed for the classification of sizing, as listed in Table 5, seven cost parameters have been taken into account as the most prevalent ones.

2.3.1 EAC (Equivalent annualized costs)

The EAC of a hybrid power system can be obtained by multiplying the total NPV of the system by the "loan repayment factor," $A_{t,r}$:

$$\mathrm{EAC} = \frac{\mathrm{NPV}}{A_{t,r}}, \tag{16}$$

$$A_{t,r} = \frac{1 - \frac{1}{(1+r)^t}}{r}, \tag{17}$$

where NPV is the net present value of the system and $A_{t,r}$ is considered to be the loan repayment factor [114], t is the number of years and r is the annual interest rate.

2.3.2 LCC (Life cycle cost)

The LCC is used for determining the most feasible alternatives and solutions among different available classifications of the HRESs. The calculation method usually considered to perform the estimation of the LCC is1)

$$\mathrm{LCC} = \mathrm{PV}_1 + \mathrm{PV}_{\mathrm{CR}} - \mathrm{PV}_{\mathrm{R}} + E + \mathrm{PV}_{\mathrm{nf}} + \mathrm{PV}_{\mathrm{O}}, \quad (18)$$

where LCC is the total LCC in present-value (PV) dollars of a given alternative; PV_I is PV investment costs; $\mathrm{PV}_{\mathrm{CR}}$ are PV capita, and the replacement costs; PV_R is PV residual value (resale value, salvage value) less disposal costs; E is the energy costs associated with the PV array; $\mathrm{PV}_{\mathrm{nf}}$ is the non-fuel operating, maintenance and repair costs of the PV array; and PV_O are other costs related to the PV array (e.g., contract costs for ESPCs or UESCs).

2.3.3 LCOE (Levelised cost of electricity)

During the financial analysis of the HRESs, the "LCOE" is a very common parameter used in the economic evaluation of these systems. It is defined as the sum of all the net present values of the unit-cost of electricity over the lifetime of a generating asset. It is often taken as a substitute for the average price producing the asset, which should obtain in a market to break even over its lifetime. A simplified method for calculation the LCOE is provided as2)

$$\mathrm{LCOE} = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}, \quad (19)$$

where I_t is investment expenditures in year t (including financing), M_t are operations and maintenance expenditures in year t, F_t are fuel expenditures in year t, E_t is electricity generation in year t, r is discount rate, and n is the life of the system.

2.3.4 Net present value (NPV)

In the field of finance, the NPV is a method for obtaining the profitability of a financial project, which is calculated by subtracting the present values (PV) of cash outflows (including initial cost) from the present values of cash inflows over a period of time. The NPV is estimated based on

$$\mathrm{NPV}(i,N) = \sum_{t=0}^{N} \frac{R_t}{(1+i)^t}. \quad (20)$$

Each cash inflow/outflow is discounted back to its PV through

$$\sum_{t=0}^{N} \frac{R_t}{(1+i)^t}, \quad (21)$$

where R_t is the net cash flow i.e., cash inflow – cash outflow, at time t; t is the time of cash flows, while i is considered as the discount rate [116].

2.4 Grid classification

The concept of the grid covers a variety of applications such as the operational and energy dimensions including smart meters, smart appliances, renewable energy resources, and energy efficient resources. Electronic power conditioning as well as the management of the production and distribution of electricity are also considered as the important aspects of the smart grid. In addition to the aforementioned issues, grid extension and connection costs are considered as important factors to integrate the renewable power sources into an existing electricity network.

HRESs are either grid-connected or off-grid. The advantage of the on-grid HRES is that, it provides the opportunity to sell the excess energy generated by the HRESs to the grid for recovering some of the costs for the energy purchased. However, the off-grid HRESs have also received a considerable amount of attention from around the globe, as they allow electricity access in remote rural communities at lower costs than on-grid systems. They are usually integrated with storage units, especially batteries. A key issue in the cost effectiveness of such systems is the battery degradation during the time that the battery is charged and discharged.

In the current research review, it has been concluded that more than 70% of the paper are the off-grid applications of the HRESs while the remaining ones are on-grid model scoping with the optimization of the HRESs. When taking into account the concept of the grid, the grid power price as well as the breakeven extension distance are typically considered during the grid analysis of the HRESs. In rare occasions (as shown in Table 5, twice), the authors have only taken into account both the off-grid and on-grid configurations of the HRESs simultaneously for investigating their performance and optimization.

2.5 Technology and energy resource investigated

During the design of the HRES, one important criterion is the correct allocation of the energy sources which are considered in the integration of the HRES. As a matter of fact, an optimized allocation of energy sources of an HRES will lead to a higher efficiency rate and lower net present cost.

1) National Institute of Building Sciences. Whole building design guide. 2017–04–27, https://www.wbdg.org/resources/life-cycle-cost-analysis-lcca
2) US Department of Energy, DOE Office of Indian Energy. Levelized cost of energy (LCOE). 2017–04–27, https://energy.gov/sites/prod/files/2015/08/f25/LCOE.pdf

One interesting conclusion derived from the evaluation of the classification drivers emphasized the existence of diverse configurations of the HRESs ranging from low numbers of the energy sources, such as PV/hydro, and wind/hydro to higher numbers, such as PV/wind/DG/battery and PV/wind/DG/hydrogen/battery (Fig. 5). In addition, one special configuration observed was the incorporation of the wood gas generator with the intermittent energy sources (solar and wind). Such a combination was rarely investigated from previously addressed research papers. It is worth mentioning that two configurations, wind/PV and wind/PV/DG were also the most frequent combinations observed from the literature review, with their frequencies being 17 and 13 respectively. As a matter of fact, the number of studies coping with the combination of wind and solar systems with integration of the battery storage were much more than the HRESs with other types of system configurations. In general, 36 research cases investigated the integration of wind and PV with battery simultaneously. Additionally, in 30-four research studies, optimization analysis for the integration of the DG with the HRES was also performed.

3 Primary and common components of the HRESs

In this section, the commonly used equipment in the design of the HRESs are discussed and elaborated.

3.1 Central control unit of the HRESs

The central control management unit plays a crucial role in the operation of the HRESs. Adequate design of the system will not just result in the enhancement of the energy production from the HRES, but its efficiency as well. Additionally, the lifetime of the battery could be increased significantly, and in the same time, the number of HRES deficit hours, the DG's operating hours and the amount of dumped power could be reduced. Some other important points, which should be considered in the management of the control system, are battery management, engine on/off cycling, maximum power point tracking of the available solar and wind energy, load management, quality of power during power generation, and the operation of different components of the HRESs [36].

3.2 Photovoltaic system

In addition to the regional resource and the cost of the fuel (as well as the fuel escalation rate), many other parameters have influenced the actual payback period of a hybridization investment. Solar PV arrays usually have a longer lifespan (more than 20 years). However, their energy yield gets slightly decreased by passage of the time. The energy yield has to be estimated in the techno-economic analysis across the lifetime of the project. PV panel manufacturers usually guarantee a 90% of the initial performance after 10 years and 80% after 25 years. Furthermore, the possibility to resort a guarantee, if it is required after a few years, remains an open question in areas where distributers are not well organizing the manufacturing processes.

The duty of a PV system is to convert the energy coming from the sun's power directly into electricity. One important primary part of the PV array, which is the smallest compartment, is the solar cell. Such cells are typically configured and adjusted in the module, which is joined in series and or/or parallel fashion to form arrays. The DC electricity produced at the terminals of the arrays can be utilized in a variety of applications, such as the DC

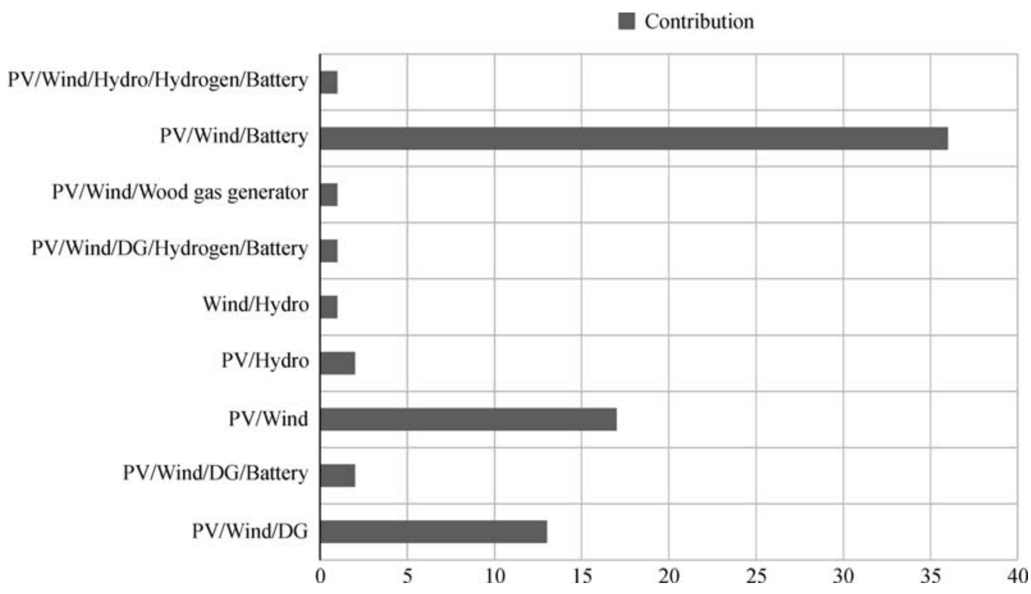

Fig. 5 The contribution of different HRESs configurations

motors or lighting systems. Figure 6 outlines the characteristics (current versus voltage, *I-V*) of a common PV system, which is nonlinear, as it is demonstrated. Different parts of the diagram for a typical solar PV-array, are categorized as series configuration, parallel configuration, and single configuration.

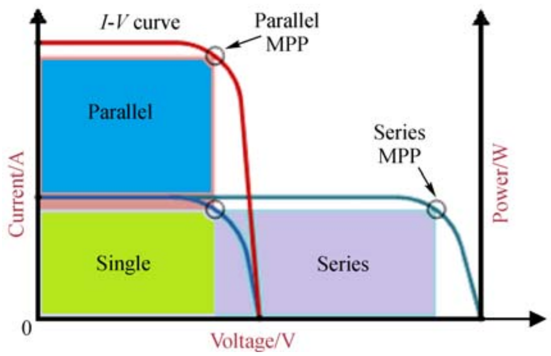

Fig. 6 The *I-V* characteristics of a typical solar PV array

The power generated by the PV array can be expressed as a function of the solar radiation and the ambient temperature as shown in Eq. (22).

$$P_{\mathrm{out}} = P_{\mathrm{r}} G[1 + K_t(T_{\mathrm{amp}} + 0.256 \times G - T_{\mathrm{ref}})]/G_{\mathrm{ref}}, \tag{22}$$

where P_{out} and P_{r} are the output power of the PV and the rated power under standard conditions respectively. Solar radiation in the standard condition (G_{ref}) is considered to be 1000 (W/m^2), and the ambient temperature T_{amb} is considered to be 25°C [86].

A related point to consider in the design of the solar cells and estimation of their performance, is the determination of the parameter values of photovoltaic (PV) cell models, which plays a big part in the design process. The key parameters representing the performance of solar cells include generated photocurrent, saturation current, series resistance, shunt resistance, and ideality factor. Estimating these parameters accurately is an essential part of a precise modeling and performance evaluation of solar cells. So far various computational intelligence methods, such as genetic algorithm, particle swarm optimization, simulated annealing, and harmony search, have been proposed for optimal estimation of solar cell parameters. Many studies have aimed to overcome the shortcomings of the conventional deterministic algorithms and to investigate the efficiency and applicability of the algorithms. Hybrid methods integrating two or more metaheuristic algorithms have also been applied lately to explore the capability of stochastic artificial intelligence algorithms for estimating the solar cell parameters. These algorithms could find relevant parameter values through minimizing the root mean square error (RMSE) as the objective function in the optimization process. Furthermore, the metaheuristic algorithms have also demonstrated a worthwhile level of applicability for estimating the solar cell parameters with a good performance [117].

3.3 Solar power conditioning unit (PCU)

A solar power conditioning unit (PCU) is a device which is intelligently designed to check and evaluate the output power of the PV panels. In the event that the energy output of the hybrid power system is sufficient to charge the battery, no power can be extracted from the primary units. However, if there is a deficit in the solar energy output afterwards, the remaining power will be taken from these units. By way of an example, if solar panels are supplying 12 A, and a 150 AH battery is connected to the system, it will extract the remaining 3 A from the grid. A PCU typically consists of the following functional units: solar charger, inverter, grid (main utility charger), output selector mechanism, battery bank, control algorithm, and the solar charger. The solar PCUs are integrated systems consisting of a solar charge controller, an inverter, and a grid charger. They supply the facility to charge the battery bank through either a solar or grid/DG set. The purpose of the PCU is to continuously monitor the state of battery voltage, solar power output, and the load[1)]. A typical solar PCU system, which is integrated for utilization in the configuration of the HRESs can be observed in Fig. 7.

Fig. 7 A typical PCU system for utilization in the configuration of the hybrid power system

1) Su-Kam Solar Inc. 2017–03–19, http://sukam-solar.com/solar-power-conditioning-unit-pcu;
Ningbo Green Light Energy Tech. Co., Ltd. Professional Solar Power Systems Supplier in China. 2017–03–27, http://www.solarpowersystemscn.com/solar-power-conditioning-unit.html

One latest and innovative research work which has received the attention of designers to adjust the performance of the HRESs is the adjustment of the performance of the solar PCU with the purpose of enhancing the efficiency of the mixed grid tied systems, as well as the off-grid systems. In such events, when the primary lines are off, the solar PCU will begin functioning to prevent power losses, and supply back-up. Obviously, the research in this aspect is still in progress to devise further innovative methods for effective utilization of the PCUs.

3.4 Maximum power point tracking (MPPT) methods

The electronic control of the PV modules can typically be managed through using the MPPT algorithms by the use of the sophisticated power electronic converters. A tracking method, which is implemented by the power electronic converters, would ramp up the operating point of the PV close to the MPP. An MPPT algorithm is commonly applied in the converters to maximize the power extracted from PV modules under varying atmospheric conditions. The utilization of the MPPT will aid to achieve the highest energy output from the PV array, thus reducing the PV array cost through decreasing the number of solar modules required to obtain the same power output [118]. Table 6 outlines a review of the latest MPPT methods, and their characteristics, which have been implemented for the PV modules.

3.5 Wind energy conversion systems (WECSs)

The current review has concluded that out of the 66 research cases, 47 research studies have included the WECSs in their configuration of the HRESs. It is important to bear in mind that utilization of those of small WTs which have a lower cut-in wind speed will result in a higher efficiency in electrical production. This will enable the higher production of wind power in areas with even a lower level of wind speed values. To estimate the power output of the wind turbine, different methodologies exist. However, the most common model is the one which uses integral form of the equation:

For a given wind regime, U and a probability distribution of that wind speed, $f(U)$; a known machine power curve, $P_w(U)$; and the mean wind machine power output, P_w can be calculated by

$$P_w = \int_0^\infty P_w(U) f(U) \mathrm{d}U. \tag{23}$$

Therefore, with a summation over N bins, the following expression could be utilized to estimate the average wind machine power:

$$P_w = \sum_{i=1}^{N_B} \frac{1}{2}(U_{i+1} - U_i)[P(U_{i+1})P_w(U_{i+1}) + P(U_i)P_w(U_i)]. \tag{24}$$

Using Eq. (22) for the average wind machine power, it is possible to calculate the annual energy captured from wind turbine:

$$E_w = P_w \times N \times \Delta t, \tag{25}$$

where N is the number of measurement periods, Δt.

If P_R is the rated power of the turbine and CF is the capacity factor, the energy generated (E_I) by the turbine in a year is

$$E_I = 8760 \times P_R \times \mathrm{CF}, \tag{26}$$

CF, which is the measure of electrical energy generated per kW of installed capacity (kWh/kW) per year, would primarily contingent upon the wind speed distribution and the design of the wind turbine, which also includes the power curve of that WT [122].

3.6 Energy storage

In the design and optimization of HRESs, an energy storage system, in most cases, a battery pack, is considered specifically when a HRES proposed is supposed to meet the electrical demand of a rural community, with no access to the electricity grid.

The lifespan of the battery bank is contingent upon many parameters, mostly those relating to the way they are operated and to external conditions, in particular the ambient temperature. For instance, the typical lead-acid batteries are designed for the applications of solar plants,

Table 6 The latest MPPT methods and their characteristics

No.	MPPT method	The involved parameters	The type of implementation	Dependency on the PV module parameters	Reference
1	Artificial intelligence	Reliant on the adopted method	Digital	Yes	[118]
2	Short circuit current	Current	Analog, and digital	Yes	[118]
3	Open circuit voltage	Voltage	Analog and digital	Yes	[119]
4	Incremental conductance (INC)	Voltage and current	Digital	No	[119]
5	Perturb and Observe (P&O)	Voltage and current	Analog and digital	No	[120]
6	Hill climbing	Voltage and current	Analog and digital	No	[121]

which usually lead to the energy loss between 15% to 20% of their lifespan, which is directly related to the number of charge and discharge cycles they can perform, for each of them it is considered to be 5 degrees above the standard temperature, which is 25°C. Furthermore, the deeper the battery is discharged at each cycle (depth of discharge), the shorter is its lifespan. This indicates that in order to reach an optimal battery lifespan, one has to install a large enough battery to achieve a suitable depth of discharge. Considering the battery cost (around 20% to 30% of total system cost), it is more desirable to design a battery bank whose operating conditions will last for 6 years minimum and ideally 8 to 10 years. Contingent upon the type, the configuration, the temperature, and other design variables of the battery, the maximum charge cycles can be between 1300 to 1500 cycles [123]. Looking more precisely through the design of the battery and its charging cycles, as a side note, in a latest research, a novel and comprehensive approach using the Harmony search (HS) optimization has been used for charge scheduling of an energy storage system (ESS) with renewable power generators to find the optimized ESS scheduling under time-of-use (TOU) pricing with demand charge. A comparison with the obtained results of the genetic algorithm (GA) has also been performed. The results of this research have suggested that the HS proposed is more efficient to save electricity cost compared to the GA method. For all the cases studied, the %-saving values of HS are also higher than those of the GA method [124].

Moving on toward the technical characteristics of the component of the battery during the design of the HRESs, it is noteworthy to mention that the two important parameters, nominal capacity Batman and the state of charge (SOC) are invariably considered during the analysis procedure. The SOC of the battery can be defined as

$$\mathrm{SOC}(t) = C_{\mathrm{Battery}}(t)/C_{\mathrm{Battery.max}}(t), \tag{27}$$

$$0 \ll \mathrm{SOC} \ll 1, \tag{28}$$

with C_{Battery} being defined as the capacity of the battery at time (t), $C_{\mathrm{Battery.max}}$ is the maximum capacity of the battery. If SOC equals one, the battery would be full; If SOC equals zero, the battery would be empty [55].

The state of charge of battery must satisfy

$$\mathrm{SOC}_{\mathrm{bat\_min}} \ll \mathrm{SOC}_{\mathrm{bat}}(t) \ll \mathrm{SOC}_{\mathrm{bat\_max,}} \tag{29}$$

where $\mathrm{SOC}_{\mathrm{bat\_min}}$ and $\mathrm{SOC}_{\mathrm{bat\_max}}$ are the limits of the SOC of the battery while $\mathrm{SOC}_{\mathrm{bat\_max}}$ is the equivalent of the nominal capacity of the storage system.

The inferior limit is given based on

$$\mathrm{SOC}_{\mathrm{bat\_min}} = \mathrm{DOD} \times C_{\mathrm{bat}_n}, \tag{30}$$

DOD represents the depth of discharge of the battery in percentage value. The total capacity of the battery relies on the number of autonomy days [55].

It bears mentioning that in most of the designed energy storage devices which are used in the configuration of the HRESs, the lead-acid battery is often employed. The energy conversion during charging as well as discharging of the battery takes place with the following reversible reaction:

$$\mathrm{Pb} + \mathrm{PbO_2} + 2\mathrm{H_2SO_4} \underset{\mathrm{charging/discharging}}{\longleftrightarrow} 2\mathrm{PbSO_4} + 2\mathrm{H_2O}. \tag{31}$$

In this regard, the modeling of the lead-acid battery for the real time analysis of the HRESs should account for the dependence of battery parameters on the state of charge, the battery storage capacity, the rate of charge/discharge, the ambient temperature, and life and other internal phenomenon, such as gassing, double layer effect, self-discharge, heating loss, and diffusion[1)].

Energy storage sizing is one of the most important stages in the design process of the HRESs. As a matter of fact, there are 4 key-element steps to be considered in battery sizing, which are battery bank voltage, days of the autonomy, depth of discharge, and temperature.

It is noted that the battery bank capacity can be estimated according to the days of autonomy expressed as [109]

$$B_r = \frac{bE_{\mathrm{acload}}}{(\mathrm{DOD_{max}})\eta_i C_t}, \tag{32}$$

where b is a constant which can be calculated as explained in Ref. [109], E_{acload} is the total AC load on the system in ampere-hour, η_i is inverter efficiency, $\mathrm{DOD_{max}}$ is the maximum permissible depth of discharge, and C_t is the temperature correction factor as allowable DOD decreases with the decrease in temperature. However, a high DOD may lead to the decrease in the lifetime of the battery.

In addition, the number of cells for the battery bank can be estimated based on the maximum battery voltage and float charge voltage expressed as

$$N_{\mathrm{cells}} = \frac{\text{Maximum voltage}}{\text{Floath charge voltage}}. \tag{33}$$

The minimum battery voltage is the minimum system voltage (including voltage drops across the cables). Furthermore, the required capacity for the cells, F_s, can be estimated according to

$$F_s = \sum\nolimits_{F=1}^{F=s} \frac{A_P - A_{(P-1)}}{C_t}. \tag{34}$$

The required uncorrected cell size F is then given by

$$F = \max(F_s)_{s=1 \text{ to } N}, \tag{35}$$

1) Critical Power Group. IEEE 485 Lead Acid Batteries for Stationary Applications. 2017–07–13, http://criticalpowergroup.com

where F is uncorrected (temperature, aging and design margin) cell size, s is the section of duty cycle being studied (containing all previous sections), N is the number of periods in the duty cycle, P is the period being analyzed, A_P is the amperes required for period P, t is the time in minutes from the beginning of period P to the end of Section S, C_t is capacity rating factor (for a given cell type, at the t minute discharge rate, at 25°C, to a definite minimum cell voltage), and F_s is the capacity required by each section.

It is noted that s can be any integer from 1 to N depending on the section being calculated and F_s is expressed in watt-hours or ampere-hours depending on which C_t is used [125].

3.7 Inverter

The inverter is a high-technology component and its replacement as a result of the failure is usually undertaken by a technician from the supplying company. It is worthy to note that the lifespan of an inverter could extend to more than 10 years. The specific complexity of the inverter often necessitates an adequate after-sales service plan (which is considered as an important source of revenue and profit for a proposed business), to be implemented to ensure the long-term sustainability of the system. Furthermore, risks, which are linked with the failure of an inverter should, therefore, be considered, especially in remote locations or countries with very limited specialized suppliers.

To prolong the runtime of an inverter, batteries can be integrated with the inverter. When attempting to add more batteries to an inverter, there are two basic alternatives to be considered, as shown in Fig. 8, which are series configuration and parallel configuration.

As a matter of fact, when the objective of the system is to produce higher overall voltage values for the inverter, the series configuration is considered during the design process. In an occasion that the lifetime of a single battery ceases, the other configured batteries will not be able to power the required load. As shown in Fig. 8, the third cell in the battery pack produces only 2.8 V instead of the full nominal of 3.6 V. With depressed operating voltage, this battery reaches the end-of-discharge point sooner than a normal pack.

On the other hand, with the parallel configuration, the capacity of the battery will be increased and more importantly, such a configuration will lead to prolonging the running time of the inverter. On such an occasion, the batteries are connected in a parallel way. This would aid ramping up the overall ampere-hour (Ah) rating of the battery set. On an occasion that the single battery is discharged, the other batteries will then discharge through it. This can eventually lead to a rapid discharge of the entire battery pack, or even an over-current and possible fire. To prevent such an event, relatively large paralleled batteries may be connected via diodes or the systems with intelligent monitoring equipped with automatic switching to isolate an under-voltage battery from the other. In a

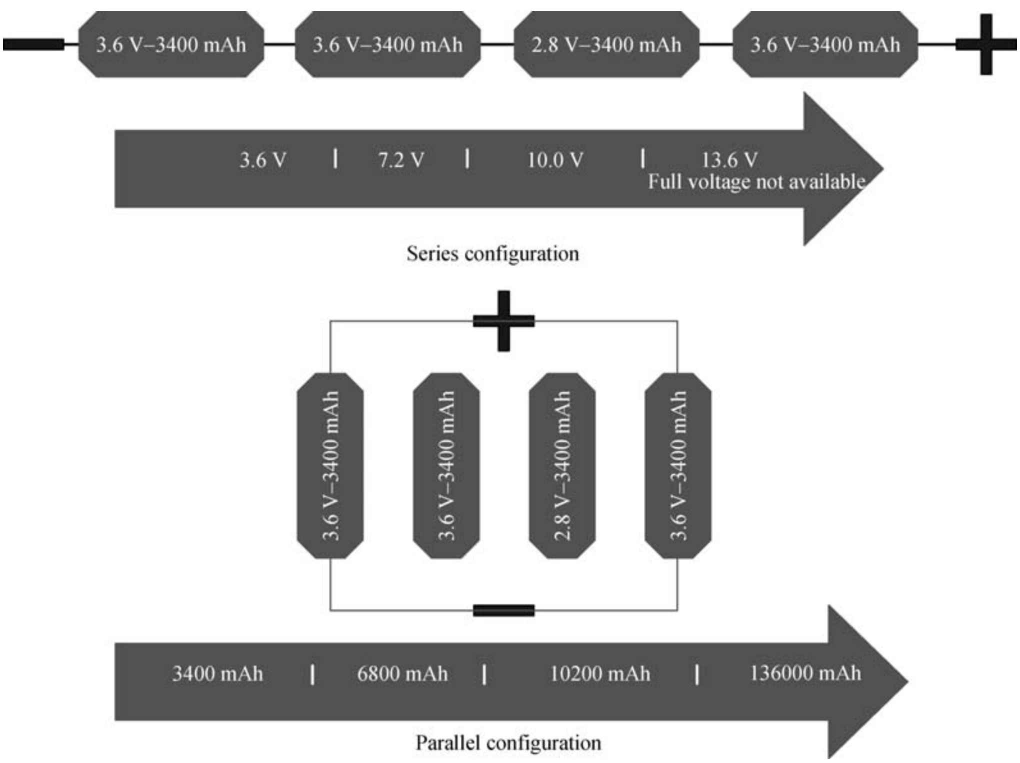

Fig. 8 The series and parallel configuration of batteries in the circuit

condition that one cell in the parallel configuration becomes weak, this will not necessarily have an effect on the voltage of the circuit. Nevertheless, it provides a low runtime operation owing to reduced capacity of battery.

3.8 Modeling of hydrogen tanks

In every important respect, it is worthwhile to mention that the hydrogen gas poses a great challenge not only to its extraction but to its storage, as well. The low density of the hydrogen gas and low boiling point of the liquid hydrogen make it difficult to store hydrogen either in a gaseous or liquid form. Therefore, for all practical purposes, the hydrogen gas is either stored as a high pressure gas or as a liquid cooled down to cryogenic temperatures or as metal hydrides where hydrogen gas bound to certain metal.

Zhou and Francois [125] represented the pressure of stored hydrogen gas using the Van der Waals equation of state for real gases as

$$P_{\text{sto}} = \frac{RT_{\text{sto}}}{V_{\text{sto}}} N_{\text{h}}, \tag{36}$$

where T_{sto} is gas temperature, V_{sto} is storage tank volume, N_{h} is the net flow rate of the hydrogen into the tank, and R is universal gas constant.

3.9 Modeling of ultra-capacitor

The ultra-capacitor (UC) which is defined as an electrochemical double layer capacitor is a low voltage energy storage device similar to a battery, nonetheless, having the capability of exhibiting an immensely high capacitance value. The overall disposable energy from a UC is expressed as

$$E_{\text{use}} = \frac{1}{2} C_{\text{total}} (v_i^2 - v_f^2), \tag{37}$$

$$C_{\text{total}} = \frac{(n_{\text{p}} \times C)}{n_{\text{s}}}, \tag{38}$$

where C is capacitance, C_{total} is the number of C in the capacitance, n_{s} is the number of UCs connected in series in each string to meet the rated voltage at the DC bus, n_{p} is the number of such strings connected in parallel to achieve the storage capacity required, v_i is the terminal voltage of the capacitor bank at the rated SOC, and v_f is the minimum voltage obtainable after discharging the capacitor limited by the specification of the DC-DC converter [126].

3.10 Diesel generator (DG)

During the design process of the HRESs, when the electricity coming from a HRESs proposed is not significant enough, the DG component can be considered in the design of the HRESs. The downside, however, would be the fact that the DG occasionally contains environmental pollutants. Examples of such pollutants are CO_x, CO_2, PM, and SO_2. Furthermore, it is imperative to notice that the DGs are typically selected on the basis of the load demand for a HRES.

The DG component, most of the time is considered in the design of the HRESs, when the electricity coming from a proposed HRES is not significant enough. On such an occasion, it is required to supply the additional electricity using the DG system. The drawback, however, is that the DG component usually releases the environmental pollutants to the atmosphere. The example of such gases are CO_x, CO_2, PM, SO_2, and other environmental emissions. Furthermore, it is important to consider that the DGs are usually selected according to the load demand of a hybrid power system.

A recent research study conducted in 2017 by Azaza and Wallin [87] expressed the fuel consumption of the DG as a function of the output power as

$$F(h) = \alpha P_{\text{r}} + \beta P_{\text{out}}(h), \tag{39}$$

$F(h)$ is considered to be the hourly fuel consumption (L/h), P_{r} denotes rated power and $P_{\text{out}}(h)$ is the electrical power produced (kW), α and β are the coefficients of fuel consumption curve (L/kW) describing the conversion ratio of the fuel to the electrical power, which are estimated to be 0.24 and 0.084 respectively. It is important to consider that in the case of proposing a renewable energy-based system, the production of electric energy would rely on the natural resources such as wind, solar, and hydro. For the off-grid installation types, it is, therefore, required to adapt storage strategies or to add one or more DGs as back-up sources [85].

To be able to perform an evaluation on the contribution of the DG component in the total share of electricity generation, the total operation hours of the generator could be determined by employing the energy deficit per month, the rated power of a selected DG, and a generator load factor.

$$h = \int \left[\sum_{k=1}^{12} \left| \frac{D(k) - N_{\text{pvp}} N_{\text{PVS}} \eta_{\text{mppt}} \eta_{\text{stri}} W \pi(k)}{q P_g} \right| \right], \tag{40}$$

where h is the number of generator hours required per year, $D(k)$ is the energy demand in the kth month, η_{stri} is the efficiency of the string inverter, η_{mppt} is the efficiency of the MPPT unit (if available), q is the load factor of the DG, P_g is the power rating of the DG selected, and N_{pvp} is the minimum parallel connection number of PV module strings (if available in the system) and is given by

$$N_{\text{pvp}} = \text{Max} \left[\int \left(\frac{\frac{D(k)}{\mu_{\text{mppt}} \mu_{\text{stri}}}}{N_{\text{PVS}} W(k)} \right) \right], \tag{41}$$

Where N_{PVS} is the serial connection number of PV modules defined by

$$N_{\text{PVS}} = \frac{V_{\text{OP}}}{V_{\text{np}}}, \tag{42}$$

where V_{np} is the nominal output voltage of the PV module and V_{OP} is the operating voltage of the PV array.

During the design of the HRESs, a proper energy balance would be required for optimum system operation as the consumption of fuel is proportional to the power being supplied by the DG. The consumption per hour of the DG can be expressed as [36,127]

$$\text{Consumption per hour} = AP_{\text{g}} + BP_{\text{ng}}, \tag{43}$$

where P_{g} and P_{ng} are the power generated and nominal power of the DG while A and B are coefficients of the consumption curve in kWh. The DG's efficiency is expressed as

$$\eta_{\text{dg}} = \eta_{\text{t}} \times \eta_{\text{mechanical}} \times \eta_{\text{electrical}}, \tag{44}$$

where η_{t} denotes the thermal efficiency of the DG, accounting for the heat loss in the DG, $\eta_{\text{mechanical}}$ corresponds to the frictional losses in the moving parts of the DG, and $\eta_{\text{electrical}}$ corresponds to the losses in the alternator. The producing efficiency which is a result of η_t and $\eta_{\text{mechanical}}$ is called as brake thermal efficiency. The overall DG efficiency varies with the amount of its power generation and it therefore operates at around 80% to 100% of its rated power or may even be controlled to operate in a constant power delivery mode [128].

To evaluate the contribution of the backup DG in the total production, the hours of generator operation can be estimated using the energy deficit per month, the rated power of the DG, and the generator load factor. It is assumed here that the generator operates at a constant load factor during hours of operation.

4 Conclusions

Climate change, which is considered as variations in the global or regional climate patterns and has particularly been started from the mid to the late 20th century onwards, is invariably contemplated as a serious global phenomenon. Moving up of the sea levels, rise of the average global temperature, depletion of the ozone concentration in the stratosphere, increased melting of the glaciers are all examples of the devastating effects of climate change, which have undoubtedly affected the human life as well as our global environment. All of these facts have considerably increased the motivation for moving forward toward the sustainable development and to protect our environment. On the other hand, a significant necessity to explore new energy alternatives for supplying the energy demand of the world is also another fundamental reason why communities and policy planners around the globe are immensely stimulated to outstandingly invest on the renewable sources of the power. Such energy sources have recently been progressing steadily in terms of different techno-economic and environmental aspects. Obviously, the emergence of novel and advanced big data tools has also revolutionized how renewable energy technologies are researched, developed, demonstrated, and deployed. By way of an example, from computational chemistry and inverse material design to adoption, reliability, and correlation of insolation forecasts with load use patterns, data scientists have brought greater opportunities to dramatically impact the future scaling of renewable energy. Forecasting methods have also made it much simpler to streamline the design process, and to meet consumer electricity demand for power as well as the reliability. On top of this, the utilization of various probability density functions (PDFs) to represent the statistics of the resources has also been evaluated. This has led to more appropriate stochastic energy scheduling modeling, and comprehensive power management strategies for load generation adequacy and security. Additionally, different optimization techniques have been analyzed lately, which has endorsed the study of optimal strategy of resource allocation to meet the load demand and ensure system security. Thereby, a robust stochastic approach with renewable energy resources and load demand has been developed, which has aided to enhance the security, reliability, and efficiency of power systems and thus, decreasing the dependency on fossil fuels.

In this regard, the development of the HRESs has become noticeably considerable. It is, therefore, imperative to adopt innovative policies to aid the designers in developing and providing new solutions for environmentally friendly power systems. It is worthwhile to notice that recently several authors have addressed the optimization and design of the HRESs by employing different novel and advanced techniques. However, there is still a considerable gap with regard to this field of research. Furthermore, it is also observed that researchers have rarely made in-depth analyses of classification drivers of the HRESs during the design and optimization process.

The purpose of the current review is to conduct a comprehensive evaluation of the common classification drivers, which affect the reliability as well as the performance of HRESs. At the first stage of this review, an evaluation of the common optimization goals and methods which are used in the design and optimization of the HRESs is performed. The number of the research cases is 98 research papers, and the preliminary purpose is to identify the commonly used techniques and methods in the design and optimization process of the HRESs. Furthermore, in order to conduct an in-depth analysis over the sizing methods which are used for sizing configuration of each of the HRESs component including the PV, wind, battery, inverter, and other key-equipment, a review of the primary methods covering the optimized indicators, the design constraints such as the LPSP, LA, FLMPVS, WLR, GDB, grid type as well as the investigated technology is performed. This review emphasizes that there are four types of categories commonly considered during the sizing of the HRESs, which are, the probabilistic, the analytical, the hybrid, and the iterative.

In the last phase of this review, different compartments of the HRESs, such as the PV, WT, battery-pack, inverter, and other related parts, which are typically considered as the primary objective in the design process are further discussed and elaborated.

The current review concludes that the cost parameter has always been considered in the design process. However, the viewpoint toward using this parameter has always been different. For instance, in many research cases, the LCOE and the LCC have been the primary optimization objectives for the cost while in some other occasions, the NPV of the system is merely taken into account in the cost evaluation of the HRESs. It also becomes clear that among all optimization algorithms utilized, the heuristic-based design methods such as the GA, PSO, and linear-based algorithms are the most commonly used ones. Furthermore, an analysis of the software tools is also carried out, which emphasizes the fact that among these tools, HOMER, Lingo, HOGA and transys are the frequently used ones in the design process. Another result of this review highlights that the number of off-grid applications are much more than the on-grid cases. This issue has necessitated a requirement of using the component of the battery inside the configuration of the HRESs. It is also concluded that, of all the studies conducted, the PV-wind-battery is the most frequent configuration of the HRESs.

It has not escaped out notice that the design and optimization of the HRESs has come a long way in terms of research and development. However, there are still considerable challenges with regard to the efficiency and the optimum utilization of these systems. Clearly, the future research has emphasized the importance of the primary design variables during the analysis and optimization of the configuration of the HRESs, and then outlining the key strategies, which could then be used for further development and optimization of the HRESs. Obviously, among all focal factors to be considered, optimization of the key variables such as the LPSP, DPSP, power loss, specific grid parameters, such as IGP, and GGP, and the cycles of the battery are going to play a bigger part in the design and optimization of the HRESs.

Specific sizing design constraints such as the state of charge of the battery, the level of autonomy, and the capacity the accumulator have also been considered as important objective functions during the design and optimization of the HRESs in future research.

Moreover, the review is also indicative of the fact that metaheuristic methods and algorithms are more efficient than the conventional methods of optimization during the design of the key parameters which affect the reliability of the HRESs. In every important respect, they can automatically manage a wide range of complexities. In particular, multi-objective optimization (MOO) metaheuristics are the most appropriate ones for optimum design of HRESs, since the HRESs models involve multiple objectives at the same time such as cost, performance, supply/demand management, grid limitations, and so forth. In general, when it comes to the heuristic-based design methods, researchers have considered a considerably higher rate of convergence to reach to the optimal solutions.

It is worthy to mention that future research directions concerning the design and optimization of the HRESs should also take into account the ongoing challenges which are encountered by decision makers. A few of these challenges include enhancing the efficiency of the solar PV arrays during the design, and configuration of the HRESs; implementing the policies, and the optimization models, with the aim of minimizing the cost of the each of the HRES components; applying innovative technologies, and methods to enhance the life cycle of the storage devices utilized in the configuration of the HRESs; designing the adequate protection devices for installation in order to enhance the safety, and the reliability of the HRESs; analysis and optimization of load fluctuations for designing the HRESs; devising innovative policies to improve the disposal of storage devices, such as the batteries and the hydrogen tanks; demonstrating, and analyzing the correlation between the energy production, and the design parameters; and designing and proposing automatic control systems with the aim of optimizing, and enhancing the efficiencies of the storage systems of the HRESs.

Notations

EIR	Energy index ratio
SOC	Battery state of charge
O&M	Operation and management
PVEC	PV electricity cost
EE	Embodied energy
LA	Level of autonomy
LST	Load shifting technique
IF	Impact factor
SEMA	Smart energy management algorithm
BBO	Biogeography-based optimization
PPOA	Power pinch optimization analysis
P&O	Perturb and observe algorithm
GSM	Global system for mobile communications
WT	Wind turbine
HPL	High priority load
PDF	Probability density function

TMC	Total manufacturing cost/€
RA	Resource availability
GC	Generator's capacity/kW
PGA	PV generator area/m^2
UAC	Useful accumulator capacity/kW
IRR	Internal rate of return/%
DPSP	Deficiency of the power supply probability/%
DG	Diesel generator
UC	Ultra capacitor
WGG	Wood gas generator
GA	Genetic algorithm
BA	Bees algorithm
SA	Simulated annealing
PA	Pinch analysis
PSO	Particle swarm optimization
ACO	Ant colony algorithm
ABSO	Artificial bee swarm optimization
SFL	Shuffled frog leap
IGP	Internal grid point
GGP	Grid generation point
BGED	Break-grid extension distance
VSI	Voltage stability index
P-ICA	Preference-inspired co-evolutionary algorithm
MOABC	Multi-objective artificial bee colony
HSS	Hammersley sequence sampling
MPC	Model predictive control
GRG	Generalized reduced gradient
MSDO	Matlab Simulink design and optimization
MCDM	Multi-criteria decision making
B&B	Branch and bound
MILP	Mixed integer linear programming
LP	Linear programming
MPPT	Maximum power point tracking
SEMA	Smart energy management algorithm
ESPCs	Energy savings performance contracts
UESCs	Utility energy service contracts
WLR	Wind power generation to load ratio
FLMPVS	Fraction of load met by a PV system
GDB	Generation demand balance
LCE	Levelized cost of energy/€
RA	Resource availability
NPV	Net present value/€
LCC	Life cycle cost/€
EAC	Equivalent annualized costs/€
AE	Applied Energy
IJHE	International Journal of Hydrogen Energy
E	Energy
RE	Renewable Energy
RSER	Renewable and Sustainable Energy Reviews
SE	Solar Energy
ECM	Energy Conversion and Management
JCP	Journal of Cleaner Production
IJEP&ES	International Journal of Electrical Power, and Energy Systems
D_{tot}	Total hours of operation/h
D_{lol}	Loss of load/%
ER_j	Emission rates of the jth technology of DG/%
I_t	Investment expenditures in year t (including financing)/€
M_t	Operations and maintenance expenditures in year t/€
F_t	Fuel expenditures in year t/€
E_t	Electricity generation in year t/kW
$A_{t,r}$	Loan repayment factor/%
μ_{inv}	Efficiency of inverter/%
S_j	Total amount of the electricity energy shortage/kW
E_0	Total energy demand of the system/kWh
$P_w(t)$	Electric power from the wind turbine/kW
$P_{spv}(t)$	Solar PV output/kW
H	Hour/h
Lps(t)	Loss of power supply during hour
N_{cells}	Number of battery's cells
P_{load}	Load demand of the HRESs/kW
G_{ref}	Solar radiation at standard condition/$(W \cdot m^2)$
P_{PV}	Energy production from the PV array/kW
P_{wind}	Power from the wind turbine/kW
P_{out}	Output power from the PV array/kW
P_r	Rated power of the PV array/kW
$P_{renewable}$	Power production from the renewable energy/kW
DPSP(t)	Deficiency of power supply probability at time t/%
DPS(t)	Deficiency power supply (DPS) at hour t/kW
E_{gen}	Energy production of the HRES at time t/kWh
μ_{inv}	Inverter efficiency of the HRESs/%
P_c	Production cost/€
GWP	Global warming potential/Million Metric Tons CO_2 Eq.
F_s	Required capacity for the battery's cells/$(A \cdot h)$
P_{sto}	Pressure of stored hydrogen gas/Pa
V_{sto}	Storage tank volume/m^3
T_{sto}	Gas temperature/°C
E_{use}	Overall disposable energy from a UC/kW
v_i	Terminal voltage of the capacitor bank at the rated SOC/V
v_f	Minimum voltage obtainable/V

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