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Review

A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system

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ABSTRACT

Electricity demand in remote and island areas are generally supplied by diesel or other fossil fuel based generation systems. Nevertheless, due to the increasing cost and harmful emissions of fossil fuels there is a growing trend to use standalone hybrid renewable energy systems (HRESs). Due to the complementary characteristics, matured technologies and availability in most areas, hybrid systems with solar and wind energy have become the popular choice in such applications. However, the intermittency and high net present cost are the challenges associated with solar and wind energy systems. In this context, optimal sizing is a key factor to attain a reliable supply at a low cost through these standalone systems. Therefore, there has been a growing interest to develop algorithms for size optimization in standalone HRESs. The optimal sizing methodologies reported so far can be broadly categorized as classical algorithms, modern techniques and software tools. Modern techniques, based on single artificial intelligence (AI) algorithms, are becoming more popular than classical algorithms owing to their capabilities in solving complex optimization problems. Moreover, in recent years, there has been a clear trend to use hybrid algorithms over single algorithms mainly due to their ability to provide more promising optimization results. This paper aims to present a comprehensive review on recent developments in size optimization methodologies, as well as a critical comparison of single algorithms, hybrid algorithms, and software tools used for sizing standalone solar and wind HRES. In addition, an evaluation of all the possible combinations of standalone solar and wind energy systems, including their assessment parameters of economical, reliability, environmental, and social aspects, are also presented.

Contents

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Nomenclature

LPSP	loss of power supply probability	LCC	life cycle cost
LOLP	loss of load probability	COE	cost of energy
LOLR	loss of load risk	LCOE	levelised cost of energy
LOLE	loss of load expectation	LEP	loss of energy probability
LOEE	loss of energy expectation	TC	total cost
UL	unmet load	TAC	annual total cost
DPSP	deficiency in power supply probability	E	total CO_2 emissions
EENS	expected energy not supplied	EE	embodied energy
ENS	energy not supplied	LCA	life cycle assessment
EIR	energy index of reliability	HDI	human development index
ELF	equivalent loss factor	JC	job creation
D	net dump energy	SCC	social cost of carbon
TED	total energy deficit	SOC	state of charge
WRE	wasted renewable energy	TPC	total precent cost
REP	renewable energy penetration	NPC	net precent cost
FEE	final excess of energy	NPV	net present value
K_I	energy fluctuation rate	$P(H)$	percentage of healthy state probability
$P(R)$	risk state probability	TC	total cost
ASC	annual system cost		
TIC	total investment cost		

1. Introduction

Electrical power is one of the most commonly sought commodities of mankind. Currently, more than 70% of the global electricity demand is supplied by burning fossil fuels, such as crude oil, coal, and natural gas [1]. With the growth of economies and world population, the demand for electricity increases and as a result the fossil fuel consumption increases. However, conventional fuel reserves are finite and depleting rapidly which require immediate attention and sustainable approaches to avoid potential energy crisis in the future. Additionally, fossil fuels account for harmful emissions, including greenhouse gasses (GHGs), which contribute to the global warming [2,3]. In the current context, these problems are addressed in several ways. One of the popular approach is to widen the public awareness on reducing energy consumption in domestic and industrial spheres and promote energy efficient technologies. Another approach is to promote renewable energy systems (RES) and develop associated technologies to make them reliable, cost-effective, environmental friendly and affordable even to the general public to use in their residential applications. The latter has drawn more attention in the research community, industries, and governments and as a result, many countries and regions have taken strong initiatives to increase their renewable energy capacity.

In Europe, the European Technology Platform for Electricity Networks of the Future, also known as ETP Smart Grids (ETP SG) produced the Strategic Research Agenda 2035 (SRA 2035) which expected that by 2020, approximately 34% of the total electrical energy consumption will come from renewable energy and will have gone more than that by 2035 [4]. The European Union (EU) council adopted the Energy Roadmap 2050 in June 2012 which declared that decarburization by 80% reduction (compared with the estimated level in 1990) of GHG emissions in European energy system will be technically and economically feasible. This can be achieved by implementing numerous strategies, such as increasing the development of renewable energy generation, which can be seen clearly where the local and small-scale generation from renewable energy sources has remarkably increased in Europe from 312 GW at the end of 2012 to 380 GW at the end of 2014 [4]. In Italy, 11.4 GW of photovoltaic (PV) power capacity had been connected to the distribution network in December 2012 [4]. In Germany, as of September 2015, RESs accounted for 47% of installed net generating capacity [5]. Furthermore, the annual energy production at about 38.850 GW comes from PVs in August 2015 keeps Germany with the largest amount of installed PV capacity in the world [5,6], and about 41.353 GW are from onshore and offshore wind turbines in September 2015 [5]. Similar trends are observed in other countries and regions such as the USA [2,7,8], with over 16 GW of installed solar power in 2014 [6]. This trend increased the total installed PV power globally to reach over 177 GW [4].

The aforementioned renewable energy capacities include large scale wind and solar systems, as well as residential PV systems. Majority of the residential PV systems work in the grid connected mode, in which excess power is injected to the grid during the day time and power is received from the grid at night. However, in remote areas where the grid extension is not feasible, HRESs are used in the standalone mode for individual houses or in microgrids (MGs) where several houses are connected to form a small power grid [9,10]. The second approach is becoming popular in islands and rural areas [11] as it provides a cost-effective alternative where power grid extensions is expensive and fuel transportation is difficult and costly [12]. Currently, the population in islands is estimated to be over 740 million worldwide based on geographic information system (GIS) analysis [13]. Another study has shown that many islands in the Indian and Pacific Oceans spend up to 30% of their gross domestic product (GDP) on conventional energy resources, such as fossil fuel [14]. In the Caribbean islands, power systems mainly depend on fossil fuel where the oil price can reach up to four times higher than the prices in the mainland [15]. In recent years, the energy demand is increasing in islands and remote areas, which means that it is not a cost-effective to keep relying on fossil fuels. Therefore, standalone HRES or MGs with RES is a promising and sustainable solution to supply the growing population and industries in remote areas and islands with clean and cost effective electrical power [14,16,17].

The intermittent nature of the environment is reflected in the electrical power generated from the RES as most of them come from the environment. For example, wind and solar energy has a strong dependency on the environmental conditions, which is considered as the major drawback of these sources. Nevertheless, this problem can be solved by combining two or more energy sources along with a back-up unit to form a HRES [18]. The combination of RES with complementary characteristics, such as wind and solar, is common in HRESs. Moreover, the integration of energy storage systems (ESSs), such as battery banks, or conventional energy sources, such as diesel generators, makes HRESs capable of providing more economic and reliable supply of electricity to a given application [18,19]. However, the high initial cost, increased maintenance cost, and different rates of depreciation are the main challenges associated with these hybrid systems [18]. Moreover, as the HRES design is affected by various factors, such as availability of energy sources and specification of sites, as well as technical, and social constraints [20–22]; they influence the power production arrangements of the system, which increases the total cost of the system [22]. In this context, an optimal sizing combination is a vital factor to achieve higher reliability with lowest costs.

The optimal design of HRESs is a complicated task since the optimal configuration depends on the knowledge of energy sources, technical specifications, environmental conditions, and load profiles [18]. Studies on modeling, configurations, planning, and optimization techniques of HRESs have been conducted for various locations and constraints [3,12,18,20,23–34]. Majority of these studies have used solar and wind hybrid systems as they are efficiently complement each other [28]. In [3], authors have considered the size optimization techniques of on-grid and off-grid solar and wind hybrid systems. In [23], authors have provided a review on optimization and control strategies used for standalone and grid-connected HES. In [27], authors have focused on modelling and size optimization for stand-alone HRESs. The article covers some of artificial single algorithms and classical methods as well. In [29], authors have provided a review on some of the optimization algorithms, operating and control strategies and energy management of standalone and grid-connected hybrid system with the feasibility of the different controllers. In [20], authors provided a review on planning, configurations, modelling and optimization of HRES for standalone applications. However, these articles have not comprehensively addressed all recent single algorithms, hybrid algorithms and software tools with critical comparison of their performances in sizing of standalone solar and wind hybrid systems for remote areas and islands. In [24], authors have provided an overview of some of the sizing algorithms and discussed the optimal sizing process of two HRESs. In [30], authors have focused only on some single artificial algorithms for standalone and grid-connected applications. In [18], authors have provided a review on the use of artificial intelligent algorithms in sizing HRES. In [12], the authors focused on integration configurations, storage system options, sizing methodologies and control and management of standalone HRES. This article provided an overview of some of the single artificial algorithm, classical algorithms and software tools. In [31], authors have provided a review on optimum design of many hybrid combinations covering some of the artificial single algorithms and software tools. In [32], authors have provided a review on multi-objective artificial algorithms considering a few combinations of standalone hybrid systems. In [33], authors have discussed the optimal sizing of different hybrid system combinations for standalone and grid-connected applications which covers some of the artificial and classical sizing methodologies. In [34], authors have focused on hybrid energy systems based on solar, wind and fuel cell energy sources covering only multi-objective optimization algorithms. In [8], authors have focused on the feasibility analysis, control, and modeling of HREs with some artificial optimization techniques.

Even though, the abovementioned literature covers a wide range of sizing optimization, a comprehensive review, putting together the recent single and hybrid size optimization algorithms and software tools with critical comparison of their performances in standalone solar and wind based hybrid systems for remote areas and islands, has not yet been reported. Given the potential of PV-WT HES, especially standalone system for remote and island areas, this article fills this particular gap by presenting a comprehensive review on the recent development in single algorithms, hybrid algorithms and software tools used for optimal sizing of PV-WT HES and assessment parameters including economical, reliability, environmental, and social aspects. Additionally, this article provides the reader with critical comparison between size optimization techniques used for standalone PV-WT HESs with different energy sources and storage systems.

The rest of the paper is structured as follows: Section 2 presents the possible solar and wind configurations and combinations for standalone application, together with a discussion their advantages and limitations. Section 3 explains data input models and the assessments used for optimal design of standalone PV-WT HESs. Section 4 reviews and lists the most recent optimization methodologies for standalone solar and wind energy systems, including single classical algorithms, single modern algorithms, hybrid algorithms and software tools. Moreover, this section presents a performance comparison of optimization algorithms as well. Section 5 presents the findings and discusses the highlighted issues in size optimization and the future trends in size optimization of standalone HRESs. Conclusion drawn from the study are also presented in Section 5.

2. Combinations of standalone solar and wind HES

The integration of RESs with other conventional energy sources (CESs) and/or energy storage (ES) devices is common in forming hybrid systems to satisfy a given load demand. For example, PV-WT combination provides more reliable power for off-grid and standalone applications compared to individual systems [20]. However, as mentioned above, this particular RES combination requires an energy storage system to be added to alleviate the supply-demand mismatch. Moreover, CESs, such as diesel generators, or modern sources, such as fuel cells, can also be added to the RES to achieve a better energy balance. Fig. 1 shows four possible configurations of such standalone solar and wind HES. Out of these configurations, the dc-coupled connection, shown in Fig. 1(a), has become popular among many researchers because of the ease of integration and the absence of power quality issues, such as harmonics and reactive power [35–43]. The blackout for ac loads in the event of a failure in the inverter stage is a major drawback of this configuration. To overcome this problem, a number of inverters can be connected in parallel with the main inverter and a fault accommodation mechanism can be employed [44]. However, these solutions increase cost, complexity, weight, and volume. The ac-coupled system, shown in Fig. 1(b), is a better solution where all the sources are connected to a common ac-bus through interfacing power electronic converters [45–48]. Even if there is a fault in an inverter, the others can continue to supply the entire load or a part of it. Nevertheless, the need for synchronization and inherent power quality issues, such as harmonics and reactive power, are the major disadvantages of this architecture [12,44]. The hybrid-

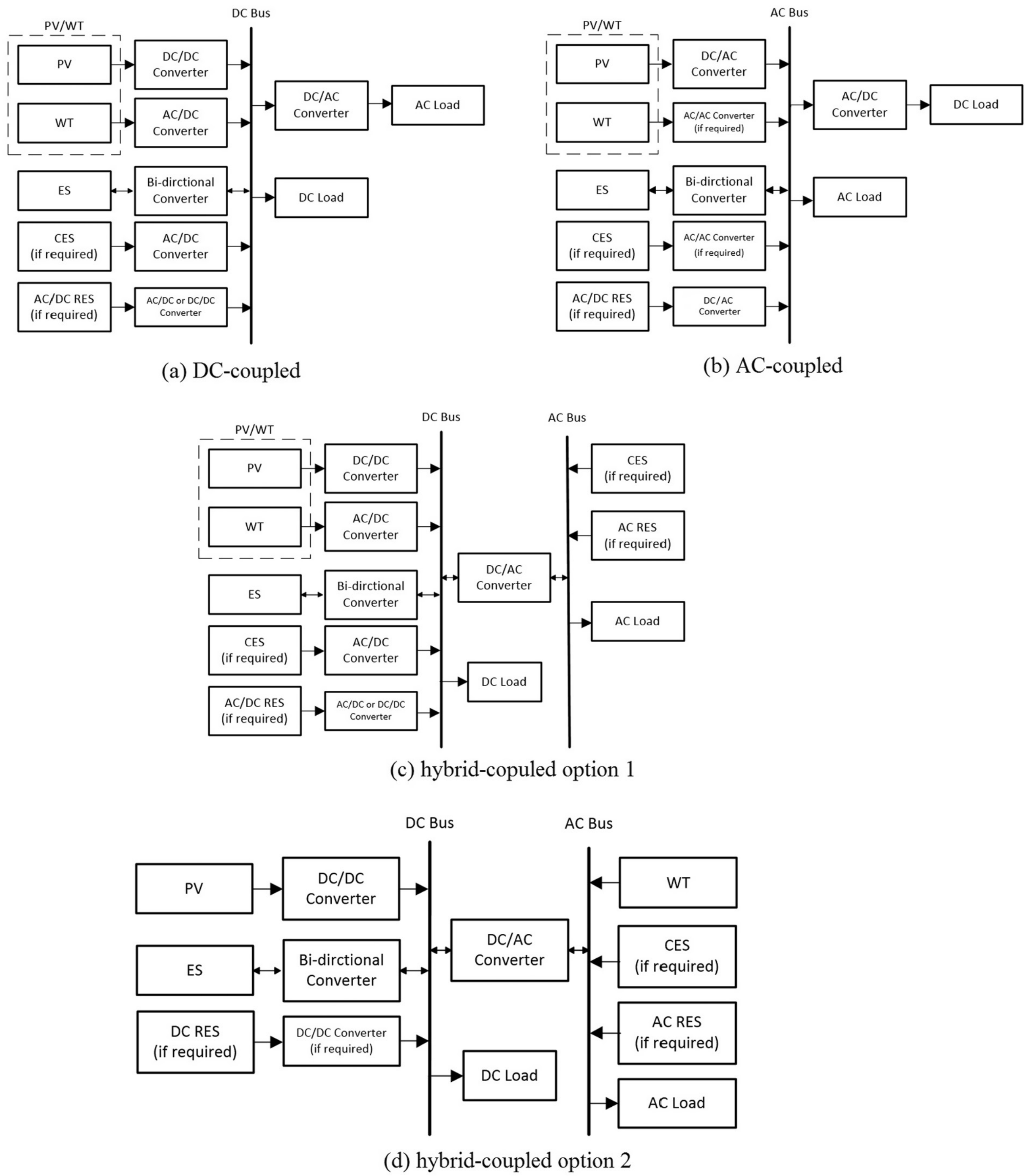

Fig. 1. Standalone PV-WT HES configurations: (a) DC-coupled, (b) AC-coupled, (c) hybrid-coupled option 1 and (d) hybrid-coupled option 2.

coupled systems, shown in Fig. 1(c) and (d), are becoming popular nowadays as they combine the advantages of both dc- and ac-coupled systems, as well as cost-effectiveness and flexibility to combined loads and sources depending on their characteristics [49–54], [17,55–58]. Moreover, they are more efficient as some of the sources can be connected to the bus directly or with a simple conversion stage [20,44]. However, there is no 'one fit all' solution in terms of the combination of RESs and their interconnection; thus, the most suitable combination and architecture should be chosen for the given application and geographical location. Commonly used solar and wind RES combinations are briefly discussed below.

2.1. Solar and wind

As solar and wind are strongly correlated to the climate, the generated power fluctuates within a large range and thus the connection to a grid or a back-up device is required to supply the required load. Therefore, the use of a single source, such as wind or solar, for off-grid applications is considered unreliable [3,59]. Moreover, wind system alone is found to be uneconomical for some standalone applications [50,57,60–63]. However, WT produces more power than PV system alone, and thus, integrating WTs with PV is important in establishing an eco-friendly HRES for diesel-free generation in standalone applications [64]. In this context, solar and wind configuration has more sense in on-grid application [65]. In off-grid application, solar and wind are usually connected with a storage system and/or other energy sources to maintain continued power supply.

2.2. Solar, wind, and energy storage

In standalone application, the widely used hybrid solar, wind and energy storage (PV-WT-ES) system combination has proven its reliability to satisfy the load requirements of remote and rural areas. In this combination, PV panels (PVPs) and WTs are connected to a storage device in order to eliminate the power fluctuation of solar and wind resources and to meet the load demand.

The hybrid PV-WT-BS system proved to be the most cost-effective combination for islands and remote area compared to PV-BS, WT-BS, and PV-WT hybrid configurations [49,66]. This has been verified through an examination with seven different heuristic optimization techniques [67]. Moreover, recent studies have shown that, PV-WT-BS HES can fully satisfy the load requirements in residential applications in remote and rural areas [49,64,68,69].

Hydrogen tank (HT) is another energy storage option. However, due to high initial costs of such storage system and the need for a fuel cell (FC) to convert the stored energy back into electricity, the hybrid PV-WT-FC energy system is considered to be less cost-effective compared to the hybrid PV-WT-BS system [50,70]. Nevertheless, the hybrid PV-WT-FC energy system is more cost effective and reliable compared with hybrid PV-FC and WT-FC systems [70,71]. Depending on the area specification such as water availability and rainfall rate, pumped hydro storage system can be a reliable energy storage option. A technical feasibility study by [72] found that a hybrid PV-WT-pumped hydro storage system is capable of supplying the full load demand in a remote area without grid support. Another storage option is the super-capacitor which has a high power density and high charge/discharge efficiency [73]. However, they have not been widely used because of their high cost and limited energy capacity compared to battery or other competitive energy storage technologies.

2.3. Solar, wind, and other renewable energy source and storage

In this combination, all energy sources combined with PV and WT are RESs, including FC, hydro generator (HG), biomass (BM), and biogas (BG). The main advantage of this combination is its minimal or zero carbon emissions. Furthermore, the use of more RES to compensate conventional sources increases job creation (JC) as it increases the manufacturing and installation rates of renewable systems [74]. FC system, including electrolyzer (EL) and HT, provides an environmental friendly and high efficiency energy system [53,75]. However, the initial cost of this system is relatively high [50]. Therefore, integrating FC and HT with a hybrid solar and wind system can effectively reduce the installation costs of FC and HT [76]. Out of the above-mentioned RES combinations the PV-WT-FC system with HT storage found to be more common as it provides a cost-effective solution compared to PV-FC and WT-FC systems [39,50,53,57,71].

In certain locations, especially in rural and remote areas, the use of an integrated renewable energy (IRE) system by utilizing as much renewable sources as possible at the site to produce electricity can provide more cost-effective option than introducing CES. For example, for villages and areas where biomass resources are available, PV-WT-BM-BS can provide a more cost-effective option than using CES such diesel generator [17] .Some other hybrid combinations, such as PV-WT-BG-BM-BS and PV-WT-BG-BM-HG-BS systems are also capable of providing cost-effective and reliable systems for remote areas and villages [74,77].

2.4. Solar, wind, and conventional energy source and storage

In this combination, PV and WT are combined with CES and ES system. Mostly, in this combination, diesel generator (DG) and battery storage (BS) are coupled with PV and WT. Although this configuration produces some emissions due to the use of CES, it is widely used in standalone application as it is more reliable in supplying the load demand. The use of BS is more cost-effective than totally relying on DG as a back-up source of PV and WT [78]. Therefore, the PV-WT-DG-BS HES is common in standalone applications as it can ensure continuity of power supply [61,79,80]. Depending on the load demand and the size of the battery, the DG can be considered as a back-up power source. The DG operates only when PV power, WT power, and BS back up are not able to supply the load demand [81]. This reduces the operating hours of the DG and thus reduces the emissions [80,82]. Therefore, PV-WT-DG-BS HES is more cost-effective and reliable for standalone application than PV-WT-DG HES [38,79,83].

2.5. Solar, wind, and other renewable and conventional energy source and energy storage

In this combination, PV and WT are combined with RESs, CES and ES. This combination is not widely implemented as it has a high initial cost and maintenance cost. However, in some locations, this combination provides a cost-effective system more than other configurations depending on the site's specifications, such as the availability of RESs, transportation of fuel, and load demand. Some studies proposed combinations such as PV-WT-DG-FC-BS-HT [84], PV-WT-DG-hydro generator (HG)-BS [85,86], PV-WT-DG-FC-BS-HT [40], PV-WT-DG-FC-bio-diesel(BD)-BS [87], PV-WT-HG-BS [88], and PV-WT-BD-HG-BS [89].

3. PV-WT HES requirements and assessment parameters

3.1. Data input

Solar irradiance and wind speed data affects the size optimization sizing results. The accuracy of the optimization results improves when the forecasted data is used instead of the data of the past years [90–93]. Moreover, the peaks of solar irradiation and wind speed influence the size optimization results by increasing the initial and operation cost values [46]. Therefore, implementing estimation and forecasting techniques to obtain a forecasted data improves the accuracy of the size optimization algorithm results. Hocaoglu et al. [93] investigated the effects of past years' solar irradiation data on the sizing of HES, and found that previous years' data cannot produce a similar loss of load probability (LLP) for a future year. Gupa et al. [90] investigated the use of historical and forecasted data on the optimization results. The authors implemented a back propagation trained artificial neural network (BPANN) for forecasting wind speed and solar irradiance. The study found that the forecasted weather data improves the optimization results. Sinha and Chandel [94] used artificial neutral network (ANN) to predict solar and wind data, and found that the predicted data by ANN are close to the measured and estimated data. Rajkumar et al. [95] applied an Adaptive Neuro-Fuzzy Inference System (ANFIS) to model a PV module and WT and thereby generate solar radiation, wind speed, and temperature datasets. To predict the output power of PV and WT, weather-generated data are used to train the neuro-fuzzy model. Nogueira et al. [96] calculated the hourly generated wind and solar power using a statistical model based on the Weibull and Beta probability density function (pdf). Khatod et al. [97] also had applied Beta and Weibull distributions for predicting the solar radiation and wind speed. Ekren and Ekren [98] used the ARENA simulation software to predict the wind speed, solar radiation, and electricity consumption distributions at a telecommunication base station in order to design a HES to supply it. The authors in [37] used autoregressive moving average models (ARMA) to model the variation of solar irradiance and Weibull distribution to model for wind speed in Kent, UK. Zhao and Yuan [82] obtained the one year hourly wind speed data through HOMER according to Weibull distribution and local meteorological data collected, and obtained the one year hourly solar radiation data on horizontal plane by using solar radiation law. Azimi et al. [99] developed a hybrid forecasting method consists of a time series analysis, a novel cluster selection algorithm and multilayer perceptron neutral network (MLPNN) to predict solar radiations. Chen [100] estimated the WT and PV power generation based on previous hourly solar irradiation, wind speed, and temperature data. Vasilj et al. [101] presented an estimation model based on Monte Carlo simulation (MCS) to estimate the power uncertainties and associated balancing and reserve power requirements of hybrid PV-WT system due to solar irradiation and wind speed uncertainties. The model uses production simulation for solar radiation and wind speed and forecast error simulation for wind speed, PV power, and load forecast error.

Not only the site energetic potential (solar radiation and wind speed) but also the load profile constitution affect the optimization results [79]. The load profile can be accomplished through measurement and load research surveys. If the load profile is not available, synthetically generated load profiles can be used. Several studies have been conducted on load profile estimation using different estimation and prediction methods [102–109]. ANN is used in [110] to generate a load profile based on its typical meteorological year 2 (TMY2) weather data. The ANN model was trained with the TMY2 weather data and the load profile data of neighboring regions is used to estimate a residential load for Gujarat, India. Cross-entropy (CE) is a non-parametric estimation method for density probability. This method has been used by [111] to estimate the pdf of the user energy consumption starting from measured data.

Given the fact that most of standalone HESs are used in remote and rural areas, the load profile data is unavailable in many cases. Therefore, increasing the research on improving the accuracy of estimation and forecasting approaches to obtain more accurate load profile data is necessary so as to increase the accuracy of the size optimization results.

3.2. Assessment parameters of PV-WT HES

There are various indicators reported in literature to assess HRES. These indicators can be broadly classified into four categories, namely: economical, reliability, environmental, and social assessments. These parameters evaluate the availability and feasibility of HES to help in the design and construction of an optimal system for a given application. Economical assessment is a main factor in determining the desirable minimum initial, maintenance, replacement, and any other future costs of a HRES. The reliability assessment evaluates the hybrid system's ability to ensure the cohesion of HRES in order to satisfy load demand. Environmental assessment evaluates the amount of CO_2 and other obnoxious emissions produced by the system throughout a given period of time. Social assessment evaluates the capability of the HES to produce energy for increasing the human development index (HDI). Moreover, it evaluates the social acceptance of installing hybrid system and job creation. The summary of the assessment parameters for standalone PV-WT HES is illustrated in Table 1.

4. Size optimization techniques

Size optimization techniques can be classified into classical techniques, modern techniques and software tools. Classical techniques use iterative, numerical, analytical, probabilistic, and graphical construction methods [3]. These methods utilize differential calculus in deriving the optimum solution [20]. Modern techniques use artificial and hybrid methods [3,23]. These methods can determine the global optimum system and has better convergence and accuracy in finding a set of optimal solutions [3,25]. The third size optimization approach for HES sizing include computer software tools. The most widely used software tool in size optimization for standalone PV-WT HES is Hybrid Optimization Model for Electric Renewables (HOMER) [23,112]. Another software, named Improved Hybrid Optimization by Genetic Algorithm (iHOGA) has been used in sizing optimization for standalone PV-WT HES [23]. Fig. 2 shows the recent size methodologies for standalone PV-WT HES.

As the HRES design is complex due to the uncertainties associated with renewable resources and other technical factors and the constraints associated with the site location and system components. Classical techniques are not efficient in solving such complex problems. Therefore, in the last decade, modern techniques that are based on meta-heuristics algorithms have extensively been used [3,113].

Sizing optimization methodologies can use either a single objective optimization (SOO) function or multi objective optimization (MOO) functions. SOO is used to find the optimum solution corresponding to the minimum or maximum value defined by the SOO function. In contrast, MOO combines two or more individual objective functions to determine a set of trade-off solutions, which allow decision makers to select the most suitable solution based on the problem requirements [32]. In this context, the use of MOO provides more efficient results as it finds the global optimum Pareto-set solutions, thereby improves the cost-effectiveness and reliability of HES combination compared to the SOO [39,42].

Most classical techniques use single algorithms with SOO function. Modern techniques use single and hybrid algorithms to solve SOO or MOO problems. Hence, modern methods are more flexible in dealing with complex optimization problems, and they provide more accurate results. An overview of the optimization techniques discussed in this paper is shown in Fig. 3.

4.1. Single algorithm

Single algorithms including classical and artificial techniques used to solve the size optimization for PV-WT HES are reviewed in the following sub-sections and the summary of each technique is presented in Table 2.

4.1.1. Classical techniques

A limited number of studies have recently been carried out using classical methods in size optimization of standalone PV-WT HES. Most of these studies are conducted using iterative algorithms [47,50,114–121]. Hosseinalizadeh et al. [50] implemented an iterative algorithm to optimize a standalone PV-WT-FC-BS-HT HES in terms of minimizing the system's total COE for four different regions in Iran. The authors used a proton exchange membrane fuel cell (PEMFC) as a back-up source to the battery storage system rather than directly supplying the load. The PEMFC operates when the charge level of the battery bank drops below the allowable level. The authors of [50] have assessed the reliability of the HES by using LOEE and LOLE as assessment parameters. In this study, it has been assumed that the value of LOLE parameter must be less

Table 1
Summary of economical, reliability, environmental, and social assessment parameters for PV-WT HES.

Assessment	Indicator	Description	Ref.
Reliability			
	Loss of Power Supply Probability (LPSP)	The probability of unmet load over the total energy produced	[67,72,83,90,95,164,165]
	Loss of Load probability (LOLP) or (LLP)	The ratio of annual energy deficits to annual load demands	[120,146]
	Loss of Load Risk (LOLR) or loss of load expectation (LOLE) or loss of energy expectation (LOEE)	The average number of hours for which the system load is expected to exceed the available generation capacity	[49,50,97]
	Unmet Load (UL)	The amount of power shortage at load that exceeds the amount of generated energy from all energy sources and stored energy in all storage devices	[72,90,113]
	Deficiency in Power Supply Probability (DPSP)	The amount of power shortage at each hour	[37]
	Expected Energy not Supplied (EENS) or Energy not supplied (ENS)	The amount of load energy not supplied during a period of time.	[49,54,97,140]
	Energy Index of Reliability (EIR)	The ratio of expected energy not supplied to the load demand	[140]
	Equivalent Loss Factor (ELF)	The ratio of the effective forced outage hours to the total number of hours	[39,52]
	Net Dump energy (D)	The total dump energy produced from RES	[55]
	Total Energy Deficit (TED)	The ratio of energy not supplied to the consumer when was requested on the total energy required	[118]
	Wasted Renewable Energy (WRE)	The energy produced by RES that cannot be stored in the storage system	[166]
	Renewable energy penetration (REP)	The ratio of total energy generated from RESs to the total energy demand of the load for a year	[47]
	Final Excess of Energy (FEE)	The difference between the accumulated electrical energy of the battery and initial electrical energy of the battery	[35]
	Loss of Energy Probability (LEP)	The ratio of the wasted energy by the scheduler model and the total load demand during a year	[42]
	Energy Fluctuation Rate (K_l)	The fluctuation rate of the entire system indicating that the optimal system output energy is matching the load demand to reduce the energy impulse of the system, increase the power supply quality and reduce the work load of the scheduler model	[42]
	Risk state probability $P(R)$	The percentage of time when generation is inadequate to supply load within a study period	[132]
	Percentage of healthy state probability $P(H)$	The percentage of time for which the system has adequate reserves to satisfy laid down reverse criteria within a study period	[132]
Economic			
	Net Precent Cost (NPC) or total precent cost (TPC) or Net present value (NPV) or total cost (TC)	The total investment, maintenance, operation and replacement costs throughout the life time of the system	[21,78,118,167]
	Total investment cost (TIC)	Include capital cost, installation cost, annual operation and maintenance cost and replacement cost throughout the system lifetime	[51]
	Life Cycle Cost (LCC)	The costs of system operation throughout lifetime. Does not include manufacturing and disposal costs	[54,55,66,131]
	Levelised cost of energy (COE) or (LCE) or (LCOE)	The ratio of the costs and total energy consumed by the load throughout the lifetime of the system	[45,121,132,167,168]
	Total annual cost (TAC) or annual system cost (ASC)	The summation of capital costs, replacement costs, operation costs and annual maintenance costs	[53,82]
	Cumulative savings	Sum of money which is saved by hybrid system for a period of time because of fuel saving	[147]
Environment			
	Total CO_2 Emissions (E) or fuel emissions	The total amount of kg of CO_2 emissions produced by the system throughout a period of time	[55,82,83,113,169]
	Embodied Energy (EE)	The energy that the hybrid system does not consume during its use, but involves the consumption of non-renewable primary energy for components manufacturing. In other words, it is the energy required by all the activities associated to a production process	[131]
	Life cycle assessment (LCA)	The assessment of all the stages of a product's life of hybrid system components including emissions associated with material manufacturing, procurement and transportation	[80]
Social Criteria			
	Human Development Index (HDI)	HDI is a country development indicator that takes into account life expectancy at birth, expected years of schooling and gross national income per capita. It depends on the consumption of electricity, so the extra energy that can be supplied by the hybrid system can improve the HDI index	[21]
	Job Creation (JC)	The jobs created of manufacturing, installation and O&M of the hybrid system components. The number of jobs created by a hybrid system depends on the combination of components, so more jobs created better hybrid system combinations	[21,74]
	Social Cost of Carbon (SCC)	Imposed by incorporating an additional cost component. It acknowledges effect of emissions from DGs on society	[132]
	Socio-demographic factor	It describes the energy consumption pattern of a household load in a certain location. This factor can be used in sizing HES by estimate how a one class of user responds to the demands from another class of user	[36]

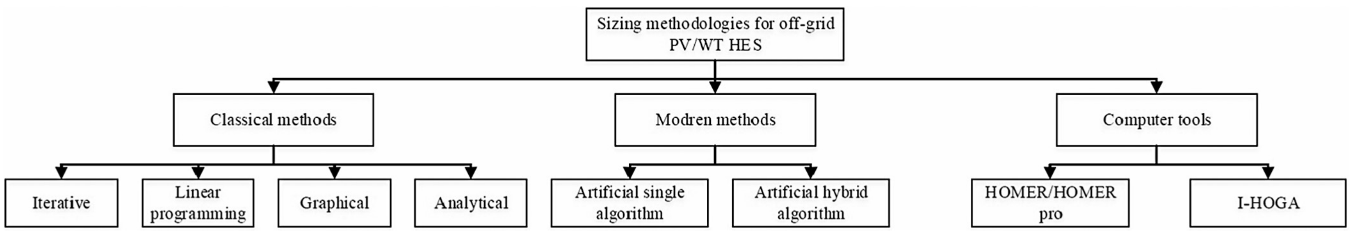

Fig. 2. Recent size optimization methodologies for standalone PV-WT HES.

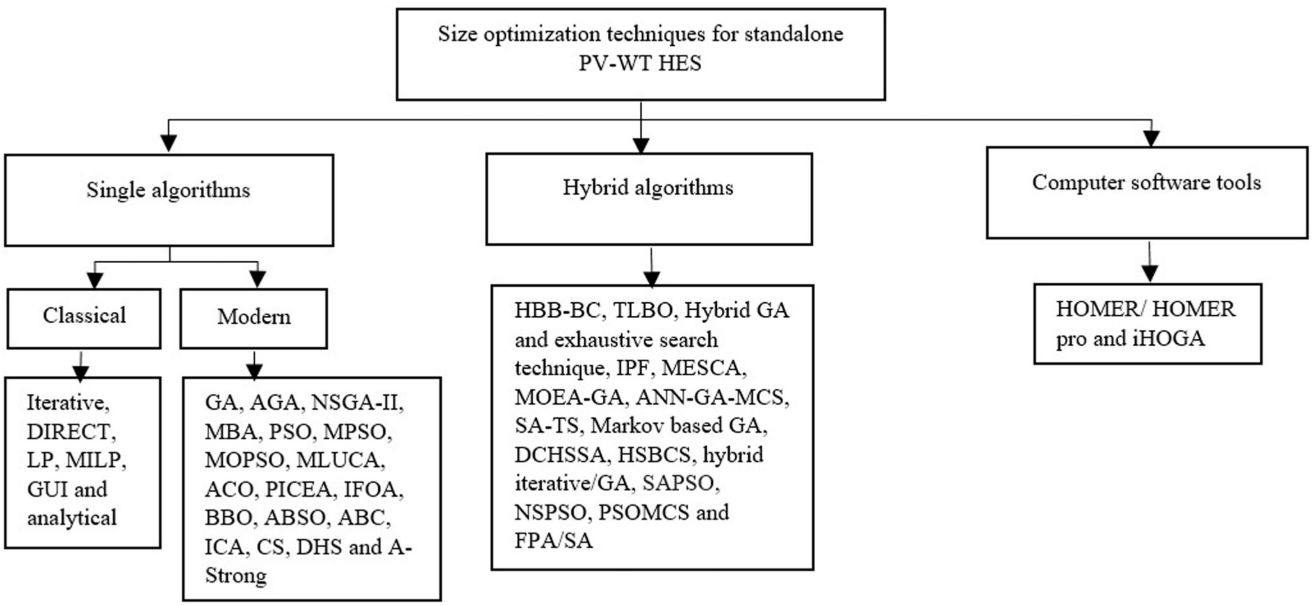

Fig. 3. Overview of the size optimization techniques discussed in this paper.

than 2% in order to achieve a reliable system. The study found that the PV-WT-BS HES is more economical and reliable without the FC system. Smaoui et al. [76] proposed an optimization methodology based on iterative technique to optimize the size of a standalone PV-WT-FC-HT HES in order to supply a desalination unit for the Kerkennah Island in South Tunisia. The optimization algorithm was implemented in two parts by calculating the FC installed and EL installed powers, and the proposed combination part which is tested to assess technical performance. The main objective of the optimization is minimizing the total capital cost of the system. The study found that the proposed HES was able to meet the load demand, and the complementary characteristics of the hybrid combination of PV and WT reduced installation costs due to decreased storage requirements. Bhuiyan et al. [47] proposed an enumeration-based iterative algorithm to optimize the component sizes for an islanded micro-grid for off-grid communities. The system consists of PV, WT, BS, and DG. The main optimization function of minimizing the LCC is used to assess the feasibility of the HES combination. The LPSP and REP are used to assess the reliability of the system by exanimating the effect of these parameters on LCC. The proposed algorithm provided lower LCC compared to HOMER. Additionally, the study found that LCC value is minimized without seasonal variations and high REP. Moreover, the LCC value is reduced when LPSP percentage is decreased.

DIRECT algorithm is an efficient deterministic algorithm in finding the global optimum of several problems. This algorithm is used in [79] to determine the optimum system configurations that the system total cost is minimized while the availability of energy is guaranteed. In this study, the reliability of the system is assessed by analyzing the battery SOC and the power balance between generation and demand. Furthermore, the study found that PV-WT-DG HES system is found to be techno-economic in meeting the energy demand of remote consumers.

A few studies have recently used linear programming (LP) in optimizing the size of standalone HES with PV and WT [96,122]. Nogueira et al. [96] proposed a methodology that uses LP to size and simulate a standalone PV-WT-BS HES for a remote rural area by minimizing the TC of the system while satisfying the load demand. The reliability of the system is assessed by using the LPSP parameter. The optimal sizing of the system is performed with six different scenarios, each with varying lengths of critical periods of predetermined amounts of consecutive hours and LPSP. Malheiro et al. [45] implemented the deterministic optimization, mixed-integer linear programming (MILP), to find the optimal mix between PV-WT-BS-DG by minimizing LCOE over a lifetime of 20 years. The optimal system was achieved with 90.0% of renewable fraction. Ferrer-Marti et al. [123] proposed a methodology using MILP and exact solve procedure with taking into account the energy demand at the consumption points and the energy resource maps to find the optimal size and location of the hybrid PV and WT system components. The objective function of the optimization is to minimize the initial system cost which is used as the parameter to assess the system. The study found that the optimal location, in addition to optimal size, reduces the initial investment costs.

Gan et al. [46] used a graphical user interface (GUI) to optimize the size of a hybrid PV, WT, BS, and DG system considering the peaks and troughs of wind speed and solar irradiance over a year.

Table 2
Selected size optimization methods that uses single algorithm.

	Energy source							Energy storage		Energy conversion		SA[a]/GC[b]	Approach	Analysis	Objective function	Constraints	Ref.
	PV	WT	DG	FC	HG	BM	BG	BS	HT	CO	EL						
Genetic algorithm (GA)	✓	✓	✓					✓				SA	Artificial	Economic, reliability and environmental	Minimize LCC, E and D	Energy balance	[55]
	✓	✓			✓	✓	✓	✓		✓		SA	Artificial	Economic	Minimize TNPC and COE	Total active sunshine area occupied by PV, total swept area for wind mills and SOC	[77]
Adaptive genetic algorithm (AGA)	✓	✓						✓		✓		SA	Artificial	Economic and reliability	Minimize installation costs	SOC, LOLP, hub height of the WT and currents balance	[100]
Non-dominated sorting genetic algorithm (NSGA-II)	✓	✓						✓				SA	Artificial	Economic and reliability	Minimize TC and DPSP	WT rotor area, PVPs area and number of batteries	[37]
	✓	✓						✓				SA	Artificial	Economic and reliability	Minimize TIC, EENS and line loss	Power flow, load capacity, DG unit capacity and inequality constraints	[130]
Controlled elitist GA	✓	✓						✓				SA	Artificial	Economic, reliability and environment	Minimize LCC, EE and LPSP	Battery capacity, PVPs installed area and WT swept area	[131]
Mine blast algorithms (MBA)	✓	✓		✓					✓	✓	✓	SA	Artificial	Economic and reliability	Minimize TAC	Number of PVPs, WTs, FC, EL, HT and inverters	[53]
Particle swarm optimization (PSO)	✓	✓		✓					✓		✓	SA	Artificial	Economic and reliability	Minimize TC	Energy balance and LPSP	[75]
	✓	✓						✓		✓		SA	Artificial	Economic and reliability	Minimize LCC	Total area of PV panels, total swept area, number of batteries and LPSP	[66]
	✓	✓	✓					✓				SA	Artificial	Economic, reliability and social	Minimize LCOE	Risk state probability, healthy state probability, SOC and number of DGs and battery units	[132]
Modified particle swarm optimization (MPSO)	✓	✓						✓		✓		SA/GC	Artificial	Economic	Minimize TIC	Power balance, controller size and inverter size	[51]
Multi-objective particle swarm optimization (MOPSO)	✓	✓		✓					✓	✓	✓	SA	Artificial	Economic and reliability	Minimize TAC, LOLE and LOEE	ELF, PV array's installation angle and energy storage capacity of HT	[39]
Multi-objective line-up competition algorithm (MLUCA)	✓	✓	✓					✓				SA	Artificial	Economic and environment	Minimize TAC and GHG emissions	Energy balance, battery capacity and number of PVPs, WTs, batteries and DGs	[80]
Ant colony optimization (ACO)	✓	✓	✓					✓		✓		SA	Artificial	Economic and reliability	Minimize TAC	Power balance, and number of WTs, PVPs, batteries, and DG	[81]
	✓	✓						✓				SA	Artificial	Economic	Minimize TC	Total energy generated and number of WTs and PVPs	[135]
Preference-inspired coevolutionary (PICEA)	✓	✓	✓					✓				SA	Artificial	Economic, reliability and environmental	Minimize ACS, LPSP and fuel emissions	WT height limits, number of PV panels, WT, battery units, and PV panel slope angle	[83]
Improved fruit fly optimization algorithm (IFOA)	✓	✓	✓					✓		✓		SA	Artificial	Economic and environmental	Minimize ATC and E	Power balance, SOC and number of hybrid system components	[82]
Biogeography-based optimization (BBO)	✓	✓	✓					✓		✓		SA	Artificial	Economic	Minimize COE	Energy balance, SOC, and number of PVPs, WTs and batteries	[90]
Artificial bee swarm optimization (ABSO)	✓	✓		✓					✓		✓	SA	Artificial	Economic and reliability	Minimize TAC	HT storage capacity and LPSP	[71]
Artificial bee colony (ABC)	✓	✓				✓		✓		✓		SA	Artificial	Economic and reliability	Minimize TC	Number of PVPs, WTs, BM, BTs and battery's SOC	[17]
Imperial competitive algorithm (ICA)	✓	✓		✓					✓	✓	✓	SA/GC	Artificial	Economic, reliability and environmental	Minimize NPC	ELF, installation angle of PV and energy stored in HT	[52]
Cuckoo search (CS)	✓	✓						✓		✓		SA	Artificial	Economic and reliability	Minimize the TC	Power balance and SOC	[49]
Discrete harmony search (DHS)	✓	✓	✓					✓		✓		SA	Artificial	Economic and environmental	Minimize TAC	Number of PVP, WT and batteries and charge value of the battery	[138]
A-Strong	✓	✓	✓					✓				SA	Artificial	Economic and reliability	Minimize the TC	Power generation, allocation and transmission within HES	[139]
Iterative	✓	✓		✓				✓	✓		✓	SA	Classical	Economic and reliability	Minimize COE	Energy balance, battery capacity and LOLE	[50]
	✓	✓		✓					✓	✓	✓	SA	Classical	Economic and reliability	Minimize capital cost	Number of PVPs and WTs, PV power generation limits and HT capacity	[76]
Enumeration-based iterative	✓	✓	✓					✓		✓		SA	Classical	Economic and reliability	Minimize LCC	LPSP and REP	[47]
DIRECT algorithm	✓	✓	✓					✓				SA	Classical	Economic	Minimize the TC	SOC, power balance and number of PVPs, WTs and batteries	[79]
Linear programming (LP)	✓	✓						✓				SA	Classical	Economic and reliability	Minimize the TC	LPSP	[96]

Table 2 (*continued*)

	Energy source							Energy storage		Energy conversion		SA[a]/GC[b]	Approach	Analysis	Objective function	Constraints	Ref.
	PV	WT	DG	FC	HG	BM	BG	BS	HT	CO	EL						
Mixed-integer linear programming (MILP)	✓	✓	✓					✓				SA	Classical	Economic	Minimize LCOE	Energy balance, and number of WTs, PVPs, batteries and DGs	[45]
	✓	✓						✓		✓		SA	Classical	Economic	Minimize initial cost	Number and location of WTs and PVPs, power balance, voltage drop limit, maximum intensity, battery charge for WT and PV controllers and electric meters at consumption points	[123]
Graphical user interface (GUI)	✓	✓	✓					✓				SA	Classical	Economic and reliability	Minimize diesel fuel use	Power balance, SOC, battery capacity and DG capacity	[128]
Analytical	✓	✓								✓		SA	Classical	Economic	Minimize production cost	Power availability of each unit, wind power generation to load ratio and generation demand balance	[97]

[a] Standalone.
[b] Grid-connected.

The objective function of this optimization is to minimize the use of diesel generator. The decision of turning on the diesel generator optimally is considered as the economical assessment parameter while power balance and SOC are used to assess the reliability of the system. The proposed method used the measured annual hourly solar irradiation and wind speed to simulate the real time operation of the hybrid system. The study found that the peaks of solar irradiation and wind speed affect the size optimization of the results.

Analytical methods are based on mathematical analysis, theoretical analysis and calculations. These methods use computational models to find the HES size as a function of its economic feasibility [25]. In these methods, a series of logical steps need to be defined and followed in order achieve the exact solution. In contrast, in numerical methods, the problem does not have a specified procedure to follow in order to achieve a set of approximated solutions [124,125]. Therefore, analytical methods required more computational time than numerical methods [33]. These methods have not been widely used in the size optimization of standalone HES consisting of PV and WT in recent years [97,126]. In [97], the authors implemented an analytical method to minimize the production cost of PV-WT hybrid autonomous system in Kandla, India. The authors validated the results obtained from the proposed analytical method by comparing it to the results obtained by MCS. In the proposed analytical method, the amount of metrological data input is less in comparison to MCS. Therefore, the proposed analytical method provided low computational burden with relatively less time compared to MCS.

4.1.2. Artificial technique

Artificial techniques have been implemented by several researches to attain the optimal size of standalone HES. These techniques can handle multiple objective problems and provide an optimal solutions set. The most recent artificial single algorithms applied for standalone PV-WT HES are discussed below.

Genetic Algorithm (GA), an evolutionary heuristic search algorithm, is one of the most powerful optimization algorithm. Numerous studies have implemented GA in finding the optimal sizing of HRE system [48,55,77,127–129]. Ogunjuyigbe et al. [55] used GA for the optimal sizing and allocation of HES in standalone mode. In this study, the authors investigated five different combinations for residential load, as well as the possibility of using small aggregated diesel generators instead of a single big-sized diesel generator. In this study, LCC, net dump load (D) and total CO_2 emissions are used to assess the system's economical, reliability and environmental aspects respectively. The study found that PV-WT-Split-diesel-BS HES is the most optimal combination in terms of the minimum LCC, COE, net dump energy, and CO_2 emissions. Additionally, the study found that the use of aggregated split diesel generators rather than a single big-sized diesel generator is more cost-effective. Rajanna and Saini [77] used GA for the optimal sizing of integrated renewable energy sources (IRES) considering several RESs and a battery storage system for four different zones in Karnataka, India. The study aims to find the optimal scenario combinations among three different scenarios based on minimizing TNPC and COE. The optimal combination of the system is found based on the two economical assessment parameters TNPC and COE. The study found that two scenarios consist of PV, WT, and BS with other energy sources are the most cost-effective. Adaptive GA (AGA) is used by [100] to optimize the size for a standalone PV-WT-BS HES because of its improved adaptability with computational simplicity to solve such non-linear problem. In this study, WT and PV generation powers were estimated based on previous hourly solar irradiation, wind speed, and temperature data for the Wuchi and Orchid islands in Taiwan. The objective function of the optimization is to minimize the total installation cost of the hybrid system. The reliability of the system is assessed by using LOLP. The optimal capacity of the standalone system was achieved for both locations in terms of total cost and reliability. Another improved version of GA, called non-dominated sorting genetic algorithm (NSGA-II), is used by [37,130] and provided promising results in solving MOO problems. Kamjoo et al. [37] applied the NSGA-II algorithm to optimize a standalone PV-WT-BS HES combination for a household load in Kent, UK. The economic and reliability objective functions of the optimization are to minimize TC and DPSP. Owing to the uncertainties arising from renewable resource which affect the DPSP value, the study used chance constrained programming (CCP) with NSGA-II to estimate the DPSP value. The proposed method provided more conservative set of solutions compared to the usage of Monte Carlo Simulation (MCS). Another study by [130] used NSGA-II in finding the optimal allocation for PV-WT-BS HES in MG. In this study finding the minimums of TIC, EENS and the losses of the line are used as economic and reliability objective functions. The results of this study revealed that the proposed hybrid system is optimized in terms of minimum investment cost and maximum reliability when combined with MG. A variant of NSGA-II, called a controlled elitist GA, is utilized by [131] to obtain the optimal combination of standalone PV-WT-BS HES for a residential application. A triple multi-objective function combination LCC, LPSP and EE is used in this study. Furthermore, the optimal size was achieved considering the economical, reliability and environmental assessment parameters.

Fathy [53] implemented mine blast algorithm (MBA) to find the optimal sizing for a HRES in terms of minimizing the ATC for Helwan, Egypt. The reliability of the system is assessed by ensuring the power balance between generation and load. The author used a real measured data of solar radiation, wind speed, and temperature to investigate the optimal size for three different combinations. The most cost-effective combination was found to be PV-WT-FC system.

Particle swarm optimization (PSO) is one of the most popular heuristic algorithms in solving non-linear optimization problem because of its simplicity, ease of implementation and fast convergence. Paliwal et al. [132] implemented PSO to find the optimal combination of PV, WT, DG, and battery units in terms of reliability ($P(R)$, and $P(H)$), social (SCC), and economic (LCOE) assessment parameters. As result, the reliability parameters are met with less storage units by using ones with large storage capacities, which reduced replacement costs. Moreover, the integration of RES with DGs reduces SCC. Sanchez et al. [75] used PSO to optimize the size for standalone PV, WT, FC, and HT for the remote residential load in Chetumal, Mexico. The objective function of the optimization is to minimize the system TC while ensuring the reliability of the system. LPSP parameter is used to assess the reliability of the system. The optimal size of components was found in terms of the lowest TC for 20 years. Askarzadeh and Coelho [66] used PSO and some of its variants to find the optimal combination among PV, WT, and BS for a remote area located in Kerman, Iran. In this study, minimizing the LCC is used as the economic objective function while LPSP is used to assess the reliability of the system. The results showed that the adaptive inertia weight-based PSO, which has a better balance between global and local search and resultant elimination of premature convergence, provided minimal LCC compared to the original PSO and its other variants. A similar study is conducted by [41] to determine the optimal renewable mix for a remote area in Iran in terms of minimizing TAC. The authors concluded that PSO-CF produces more promising results compared to PSO, other PSO variants, and other artificial algorithms. Hassan et al. [51] proposed a modified PSO (MPSO) to find the optimal combination of both standalone PV/WT/BS HES system and grid connected PV-WT HES. The economic objective function of this optimization exercise was to minimize the TIC of the system. The proposed algorithm provided the optimum TIC for the standalone mode. Bghaee et al. [39] used multi-objective PSO (MOPSO) to optimize the economical and reliability aspects of HES comprised of PV, WT, FC, and HT for 20 years. The main economic and reliability objective function of the optimization is to minimize the TAC, LOLE and LOEE of the system. The reliability of each component directly affects the annual cost of the entire system. Therefore, by examining the effect of each component outage on the whole system's reliability and cost authors optimized the sizing for different cases. Borhanazad et al. [133] implemented MOPSO to find the optimal sizing for a PV, WT, DG, and BS micro-grid for three different locations in Iran. The optimal combination is achieved by minimizing COE and LPSP. Safar et al. [134] used PSO to optimize the size for a standalone PV-WT-BS-FC system to make the HES economical with high reliability. The study used fuzzy logic controller to regulate energy flow on HES. The membership functions of FLC are then optimized by PSO. The study found that a well optimized FC system improves the life time of the batteries by reducing the variation in SOC.

Shi et al. [80] used a multi-objective line-up competition algorithm (MLUCA) to optimize the size of a standalone PV-WT-DG-BS HES in terms of economic and environmental aspects. The economic and environmental objective function of the optimization is to minimize TAC and GHG emissions of the system. The authors first introduced an improved power management strategy to improve the battery utilization and then implemented MLUCA algorithm to find the best combination of components that can satisfy the load demand. The authors found that the proposed algorithm incurred high cost and an optimum combination in terms of minimum GHG emissions.

Ant colony optimization (ACO) is a metaheuristic optimization technique with inherent capability of parallel computing, such that it can solve complex problems with dynamic behavior. Suhane et al. [81] applied ACO to find the optimal mix of PV, WT, BS, and DG in terms of minimizing TAC for a village in India. The reliability assessment parameter LCOE, which has good overall performance with only 2% unmet load, is found to be much less than the COE per unit for DG. Fetant and Khorasaninejad [135] employed ACO for continuous domains (ACO_R) based on integer programming to find the optimal mix of PV, WT, and BS system by minimizing TC (capital and maintenance). The reliability of the system is assessed by ensuring the power balance between generation and load. The minimum TC achieved for wind standalone system is $ 5652.65, followed by the hybrid of 20 PVPs, 2 WTs, and 9 battery units at $ 6429.19. In this study, ACO_R provided the optimal solution of the total costs with lower convergence iterations and time compared to GA and artificial bee colony (ABC).

Preference-inspired coevolutionary algorithm (PICEA) that uses goal vectors is a search technique which can solve complex multi-objective optimization problems. The idea of this algorithm is to coevolve multiple sets of preferences during the optimization process in order to provide different Pareto front subsets to the decision maker [136]. Shi et al. [83] implemented PICEA to design the size of standalone HES. The proposed methodology is developed to minimize ACS, LPSP, and E of a standalone PV-WT-BS-DG HES. The optimal combination is achieved with 0% LPSP and ACS of $ 8200.79.

Fruit fly optimization algorithm (FOA) is a heuristic evolutionary computation method used in finding global optimization. Zhao et al. [82] used an improved FOA (IFOA) algorithm for the optimization design of standalone PV-WT-BS-DG HES in Dongan island in China. An economic and environmental multi-objective function is utilized in the optimization that combines TC and E as assessment parameters. The study aim to find the optimal size combination in terms of minimal TC and E. The study found that with less number of WTs and battery units, better total cost, and increased CO_2 emissions can be achieved. The most economical system in terms of TC produces 5087.39 kg/year of CO_2 emissions, whereas the least economical combination is free-carbon emission.

Biogeography-based optimization (BBO) is a population-based evolutionary method. Few studies that use BBO to optimize the size of HES consisting of PV, WT, and other sources and storages have been conducted [90,137]. Gupta et al. [90] implemented BBO to find the optimal combination of a standalone PV- WT-DG-BS HES in terms of minimizing COE. The power balance between generation and demand is considered to ensure the reliability of the system. In this study, ANN is used to forecast weather data. Optimal sizing is achieved using the forecasted data, as these improve the quality of optimization results more than the previous year's data.

Artificial bee swarm optimization (ABSO) is a metaheuristic algorithm that employs different types of bees to amend their positions in escaping local optima and finding a global solution. Maleki and Askarzadeh [71] implemented ABSO to find the optimal mix of HES components in terms of the minimum TAC. In this study, LPSP is used to assess the reliability of the system. The optimization results proved that PV-WT-FC is the most cost-effective system with 0% $LPSP_{max}$.

Singh et al. [17] used artificial bee colony (ABC) to determine the optimal combination of a PV-WT-BM-BS HES in order to achieve a cost-effective and reliable HES for an isolated small village in Patiala in Punjab, India. The economic objective function of the optimization is to minimize the ASC of the system. The reliability of the system is assessed by finding the effect of failure of any generation unit of the system. The authors implemented ABC and compared its performance with HOMER and PSO. The optimal combination is achieved with an annual system cost of $ 63,006.

Imperial competitive algorithm (ICA) is an evolutionary algorithm that can solve non-linear and multi-objective problems. Gharavi et al. [52] implemented ICA to optimally design a standalone and grid-connected HES that includes PV-WT-FC and electrolyzer (EL) while considering reliability (LOEE, LPSP and ELF), economic (NPC), and environmental (E) assessment parameters. The optimization method is implemented by first solving the multi-objective function using fuzzy logic and then employing ICA for optimization purposes. The study found that the grid-connected system is more cost-effective, but it has high CO_2 emission levels compared with standalone mode.

Cuckoo search (CS) is a metaheuristic algorithm that can address complex and multi-objective optimization problems. Sanajaoba and Fernandez [49] applied CS for optimal sizing relative to the TC of three different combinations for a remote area in India. The reliability is assessed by quantifying LOLE. The study found that the standalone PV-WT-BS HES provided the most cost-effective and reliable system than other HES combinations. Additionally, the study revealed that CS provides better-quality solutions compared with other evolutionary algorithms in HES sizing.

Maleki and Askarzadeh [138] used discrete harmony search (DHS) to find the optimal size combination system among PV, WT, BS, and DG in terms of minimizing TAC and total emissions. The total emission parameter consist of the total emissions of CO_2, SO_2 and NO_2 .The system components are modeled based on the measured solar irradiation and wind speed data for Rafsanjan, Iran. The authors found that the optimal combination is WT-DG-BS which is followed by the PV-WT-DG-BS system.

Stochastic trust-region response-surface (STRONG) method is a meta-model algorithm based on response surface methodology (RSM) and the classic trust-region method. Chang and Lin [139] implemented A-STRONG method, which modified the STRONG method coupled with MCS to find the minimum TC for a standalone PV-WT-BS-DG HES. The balance between power generation and demand is used to assess the system reliability. The optimal combination is achieved by considering power generation allocation and transmission.

4.2. Hybrid algorithm

Artificial single-optimization algorithms provide an efficient and accurate set of optimal solutions with relatively less convergence and fast computational time. However, as PV-WT HES is rapidly growing especially for islands and remote areas, there is a need for even more accurate and highly advanced optimization approaches. Therefore, hybrid algorithms have recently been extensively applied for the sizing optimization of standalone PV-WT HES. Hybrid algorithm is a combination of two or more single algorithms (modern and/or classical); this combination assumes the advantage of the complementary characteristics between the algorithms to solve complex optimization problems with different linear and non-linear constraints.

Ahmadi et al. [54] implemented the hybrid big bang–big crunch (HBB-BC) algorithm to optimize the size of a standalone hybrid PV-WT-BS system in terms of minimizing the TPC of the system. ENS is used as the reliability assessment parameter in the optimization problem. The proposed HBB–BC method used PSO and mutation operator in order to prevent the trap into the local optimum value. The proposed algorithm has successfully found the optimal combination that can fully satisfy the load demand for different ENS values.

Hybrid teaching-learning-based optimization algorithm (TLBO) is a new heuristic population-based optimization with population size and number of iteration parameters. Cho et al. [38] used improved TLBO by utilizing a clonal selection optimization to find the optimal combinations for the standalone PV, WT, DG and BS system in Jeju island in South Korea with economical and reliability aspects. The economical assessment parameters used in this optimization are TAC and fuel cost while the reliability assessment parameter is LPSP. In this study, the authors used TLBO to search for the global optimal solution, and then the optimal solution is selected through the clonal selection method. Optimal sizing is achieved with a 0% LPSP and an $ 89,400 TAC.

Tito et al. [36] applied a hybrid GA and an exhaustive-search technique optimization method to size a standalone hybrid PV, WT, and battery system considering socio-demographic factors in terms of minimizing TC and ensuring system reliability to satisfy load demand. The reliability parameter used in the optimization problem is LPSP. Socio-demographic factor is used in this optimization as a social assessment parameter. The study investigated the effect of socio-demographic factors in sizing HES using the examined energy usage patterns of six different electrical users and their influence on the size of HES. The six user patterns are constructed based on 239 load profiles using Kohonen probabilistic neutral network. The authors found that the optimal size of one user at 0% LPSP cannot be exactly similar to that of other users. In this case, the generation and storage capacity should be increased to ensure that the system can meet all the load requirements of users, thereby increasing system costs.

Iterative-Pareto-Fuzzy (IPF) technique is an evolutionary algorithm that integrates the iterative, Pareto and fuzzy technologies to solve single and multi-objective optimization problems. Mukhtaruddin et al. [140] used IPF to find the optimal-mix combination of a standalone PV-WT-BS HES for Kuala Terengganu, Malaysia. EENS, D and EIR parameters are used to assess the reliability of the system while TC is used to assess the economics of the system. The optimization results provided the optimal compromised solution in minimizing TC and D while maximizing system reliability. Additionally, minimizing the unutilized excess power generated from RES yields is found to reduce TC. Abdelhak et al. [141] proposed the determination of the optimum size of hybrid PV-WT-BS system using long-term wind speed data and estimated solar irradiation. The optimum size is achieved based on the objective function of minimizing the total cost of the system.

Zahboune et al. [35] proposed the modified electric system cascade analysis (MESCA) optimization method, which combines electric system cascade analysis (ESCA) and power pinch analyses (PoPA) to derive the optimal combination of a standalone PV, WT, and BS HES in Oujda, Morocco. The main objective function of the optimization is minimizing TAC of the system. LPSP and FEE are used in the optimization to assess the reliability of the system. The optimization process is implemented in two parts by calculating the number of PVPs, WTs, and battery units based on the hybrid cascaded table (HCT) and the allowable loss of power supply (LPSP), which checks the results of the first part by computing the obtained value of LPSP with analysis time and the difference between the desired LPSP and obtained values. The optimal design is achieved with 8 WTs, 26 PVPs, and 8 battery banks with TAC of € 2391.

Dufo-Lopez et al. [21] proposed a hybrid method by combining MOEA and GA. The authors applied this hybrid method to optimize the size of a standalone hybrid PV, WT, DG, and BS system. In this study, the social parameters HDI and JC are considered for the first time in the size optimization of HES. HDI depends on the annual electrical consumption per capita, whereas JC is related to direct and indirect jobs in manufacturing, installation, and operation and maintenance of HES. The optimization process is conducted in two parts: The first part implements MOEA for component sizing in terms of minimizing NPC and maximizing HDI and JC, and the second part applies GA to optimize the control strategy in terms of NPC. The authors found that HDI can be maximized by increasing the utilization of excess energy from renewable sources to serve loads rather than dump load, hence minimizing NPC. Additionally, JC can be increased when the number of components increased in the hybrid system.

Lujano-Rojas et al. [142] proposed a hybrid MCS- and ANN-based GA optimization algorithm to find the optimal sizing for a hybrid PV-WT-DG-BS system in terms of cost and reliability for the Zaragoza area in Spain. NPC is used to assess the system economically and ENS is used to assess the system's reliability. The authors used a probabilistic method MCS to solar radiation and wind speed time series and then used generated data to train ANN-based GA. The proposed method was able to find the optimal combination of HES in a reasonable manner under conditions of uncertainty.

Katsigiannis et al. [87] proposed a hybrid simulated annealing (SA)-tabu search (TA) algorithm to optimize the size of a hybrid system for the Chania region in Greece. As SA has rapid convergence time in the neighborhood of optimal solutions and TS has high efficiency in finding the best solutions in a given neighborhood, the hybrid combination of the advantages of both algorithms yields enhanced results in dealing with the problems of having large number of diesel generator options and uncertainty in the values of many imported input parameters. The optimization objective function is to minimize the COE generated. The results showed that the proposed algorithm improved the solution quality without increasing the number of required simulations.

Markov-based GA is presented by [143] to determine the optimal size of hybrid PV-WT-DG units in terms of minimizing the TC. The environmental parameter considered in the optimization is E while the reliability parameter is LOLP. The authors used fuzzy-c-means (FCM) to cluster the operation states for PV, WT, and load and the Markov model to model the PV, WT, and load. Based on the models established by the Markov model, GA is then employed to find the optimal sizing for the system components. The authors concluded that the investment costs increase and fuel costs decrease with low CO_2 emissions and low LOLP values.

Askarzadeh [144] proposed a discrete chaotic harmony search-based simulated annealing algorithm (DCHSSA) as a discrete meta-heuristic optimization technique that combines chaotic search (CS), harmony search (HS), and simulated annealing (SA). The author used the proposed optimization method to find the optimal size combination for a standalone PV, WT, and BS system in terms of minimizing TAC. The reliability of the system is assessed by ensuring the energy balance between the generation and load. The proposed method has successfully found the optimal size of HES which comprised of 2 PVPs, 2 WTs, and 58 batteries.

Maleki et al. [145] proposed harmony search-based chaotic search (HSBCS) to optimize the size of a hybrid PV-WT-BS system with reverse osmosis (RO) for a remote area in Iran. The authors used ANN for the solar and wind forecasting and HSBCS for the optimal sizing of the system components. The objective function of the optimization is minimizing LCC of the system. The reliability parameter used in this optimization is LPSP. Three hybrid combinations are examined, and it was found that PV-BS with RO provides the lowest LCC at $ 6120 followed by the PV-WT-BS system with RO at $ 6550 LCC.

Khatib et al. [146] implemented an optimization methodology using the iterative method and GA to optimize the size of a standalone PV, WT, and BS system for Kuala Terengganu in Malaysia in terms of LPP and TC. In this study, the authors used iterative algorithm to generate a set of possible configurations of HES components, and GA to then determine the optimal configuration among the set of configurations obtained from iterative algorithm. In addition, the authors investigated the optimal tilt angle of the PV array and optimized the size of the HES inverter using iterative method. Size optimization is accomplished at different LPP values based on available daily wind speed and solar radiation.

Zhou and Sun [73] proposed an improved simulated annealing particle swarm optimization (SAPSO) algorithm to optimize the size of PV, WT, BS, and super-capacitor (SC) by minimizing the system LCC. The power balance between generation and load is used to assess the reliability of the system. The authors combined the improved SA with improved PSO to enhance the search ability and accuracy of the size optimization solutions. The proposed algorithm can find the optimal cost of the system with a total cost of $ 5839.72.

Ma et al. [42] adopted natural selection particle swarm optimization (NSPSO) by combining PSO with the selection strategy of GA to improve the precision of the optimal results. LCC parameter is used to assess the economics of the system while LPSP, K_I and LEP parameters are used to assess the system's reliability. A single-objective optimization is initially performed to optimize LCC and then a multi-objective optimization to optimize the full life cycle, LPSP, LEP, and K_I of PV-WT-BS HES. The authors introduced a penalty function to realize the constants of LPSP and a weight coefficient transformation method to embody the weighting factors of LCC, LEP, and K_I.

Maleki et al. [43] used particle swarm optimization-based Monte Carlo simulation (PSOMCS) to optimize the size of a PV-WT-BS HES while considering the solar and wind uncertainty calculation for all possibilities. TAC parameter is used to assess the economics of the system while power balance between generation and demand is used to assess the system's reliability. The authors implemented the optimization for three different hybrid combinations using measured solar irradiation and wind speed data. It was found that the hybrid WT-BS has the lowest TAC at $ 17,9472.67 followed by the hybrid PV-WT-BS system with a TC of $ 18,132.69. However, the authors concluded that the hybrid PV-WT-BS system is more reliable than the WT-BS system as it reduces the probability of having no wind generation.

Tahani et al. [147] developed hybrid flower pollination algorithm (FPA) and SA algorithm to find the optimal renewable mix with increased reliability and maximum cumulative savings. Cumulative savings is used to assess the economics of the system

Table 3
Size optimization using hybrid algorithm.

Method	Energy source					Storage system			Energy conversion		SA/GC	Analysis	Objective function	Constraints	Ref.
	PV	W	DG	FC	BD	BS	SC	HT	CO	EL					
Hybrid Big Bang–Big Crunch (HBB-BC)	✓	✓				✓			✓		SA	Economic and reliability	Minimize TPC	Number of hybrid system components, ENS and charge quality of the battery	[54]
Hybrid teaching-learning-based optimization algorithm (TLBO)	✓	✓	✓			✓					SA	Economic and reliability	Minimize TAC, LPSP, and fuel cost	Number of PVPs, WTs, batteries, and DGs and charge value of the battery	[38]
Hybrid GA and exhaustive search technique	✓	✓				✓					SA	Economic, reliability and social	Minimize TC	Number of hybrid system components, PV tilt angle (β) and wind generator installation height (h)	[36]
Iterative-Pareto-Fuzzy (IPF)	✓	✓				✓					SA	Economic and reliability	Minimize the TC	EENS, EIR and dump load size	[140]
Modified electric system cascade analysis (MESCA)	✓	✓				✓					SA	Economic and reliability	Minimize TAC	LPSP	[35]
Multi-objective evolutionary algorithm (MOEA) and GA	✓	✓	✓			✓			✓		SA	Economic and social	Minimize NPC and maximize HDI and JC	Power balance, excess energy, SOC	[21]
Hybrid ANN, GA and MCS	✓	✓	✓			✓					SA	Economic and reliability	Minimize NPC	Probability of ENS limit and NPC	[142]
Hybrid SA-Tabu search (SA-TS)	✓	✓	✓	✓	✓	✓			✓		SA	Economic and reliability	Minimize cost of energy	Initial cost, UL, capacity storage, fuel consumption, renewable fraction and components' size limitation	[87]
Markov based GA	✓	✓	✓								SA	Economic, reliability and environmental	Minimize total cost	Number of PVPs, WTs and DGs, LOLP and CO2 emissions	[143]
Discrete chaotic harmony search-based simulated annealing algorithm (DCHSSA)	✓	✓				✓					SA	Economic and reliability	Minimize TAC	Number of PVPs, WTs and batteries and DOD	[144]
Harmony search-based chaotic search (HSBCS)	✓	✓				✓			✓		SA	Economic and reliability	Minimize LCC	LPSP, swept area of WT's blades, total area occupied by PVPs and number of batteries	[145]
Hybrid iterative/GA	✓	✓				✓			✓		SA	Economic and reliability	Minimize the system cost	Energy balance, LLP and capacity of PV array, WT and battery	[146]
Simulated Annealing Particle Swarm optimization (SAPSO)	✓	✓				✓	✓				SA	Economic and reliability	Minimize LCC	SC charging and discharging, power surplus and power loss	[73]
Natural selection particle swarm optimization (NSPSO)	✓	✓				✓					SA	Economic and reliability	Minimize LPSP, LCC, LEP and K_I	Number of type 1 and 2 of PVPs, type 1 and type 2 of WTs and batteries	[42]
Particle swarm optimization based Monte Carlo simulation (PSOMCS)	✓	✓				✓					SA	Economic and reliability	Minimize TAC	Number of PVPs, WTs, batteries and SOC	[43]
Hybrid (flower pollination algorithm) FPA/SA algorithm	✓	✓				✓					SA	Economic and reliability	Minimize LPSP and maximize cumulative savings	PVP tilt angle, number of PVPs and number of batteries	[147]

Table 4
Size optimization by using software tools.

Software	Energy source							Energy storage		Energy conversion		SA/GC	Location	Analysis	Factors	Key points	Ref
	PV	WT	DG	FC	HG	BG	BM	BS	HT	CO	EL						
HOMER pro	✓	✓	✓					✓		✓		SA/GC	Shiraz, Iran	Techno-economic and environmental	COE, NPV, internal rate of return (IRR), RF, CO_2 emissions	• Hybrid PV-WT-DG-BS system found to be the most optimal system in off-grid application where COE and RF of 9.3–12.6 c/kW h and 0–43.9% respectively with maximum reduction of CO_2 emissions compared to other combinations	[78]
	✓	✓						✓		✓		SA	Oujda, Morocco	Techno-economic	NPC, RF and annual capacity shortage	• PV-WT-BS HES was successfully optimized to meet the load demand with 26 PVPs (3.12 kW), 5 WTs (2 Kw total), 8 batteries (5 kWh each) and 1.5 kW converter	[35]
HOMER	✓	✓	✓					✓		✓		SA	Kuakata, Bangladesh	Economic and environmental	TNPC, COE and exhaust gas emission	• Achieved the optimal size combination with zero emissions	[61]
	✓	✓	✓					✓		✓		SA	Three remote villages in Colombia	Techno-economic	NPC	• 99% of renewable fraction and minimum emissions were achieved with PV-WT-DG combination for Puerto Estrella village • PV/DG combination provides more economical system for Unguia and Jerico	[62]
	✓	✓	✓					✓		✓		SA	KLIA Sepang Station, Malaysia	Economic and environmental	NPC, COE and CO_2 emission	• 29.65% reduction in NPC compared to conventional power plant • 25% and 16 tons reduction in CO2 and GHG emissions compared to conventional plant	[56]
	✓	✓	✓					✓		✓		SA	Adrar village, Algeria	Techno-economic	NPC	• The configuration provides 69.4% of energy generated by PV and WT while 30.6% by DGs • The proposed configuration can replace or reduce the use of DG in remote areas as it is capable to meet consumers need	[153]
	✓	✓	✓					✓		✓		SA	Rural health clinics in six zones, Nigeria	Techno-economic	NPC, LCOE and (RF)	• Optimum tilt angle was considered and calculated for the six areas in order to increase the performance of PVPs • The PV-WT-DG-BS HES is considered optimum at Sokoto, Maiduguri, Jos and Enugu • PV-DG-BS is considered ideal at Iseyin and Port-Harcourt • Sites with high solar and wind resources (such as Jos) provided the lowest NPC and COE	[154]
	✓	✓	✓		✓			✓		✓		SA	Tioman island, Malaysia	Techno-economic	TNPC, COE, RF, CO_2 emission, diesel generator operating hours and dispatch strategy	• PV-HG-DG-BS HES is the most cost-efficient with lower carbon emissions compared to HG-DG-BS hybrid system • The PV-WT-HG-DG-BS HES has a larger generation capacity but slightly higher NPC compared to other HES configurations	[85]
	✓	✓	✓	✓				✓	✓	✓	✓	SA/GC	Telecom load, Chennai, India	Economic, technical and environmental	TNPC, COE and Capacity Shortage	• Seven combinations of HES were examined • PV-WT-BS HES provided the second lowest NPC among the seven combinations and it is found to be technically feasible with zero emissions	[40]
	✓	✓		✓				✓		✓	✓	SA	Bozcaada Island, Turkey	Techno-economic	NPC and COE	• Two combinations were examined; WT-BS-FC-HT hybrid system and PV-WT-BS-FC-HT HES • PV-WT-BS-FC-HT HES provided lower NPC and COE by reducing the HT capacity which reduced the capacity of other components	[57]
	✓	✓						✓		✓		SA	Remote island in Hong Kong	Techno-economic	NPC and COE	• The DG can be replaced by 100% wind and solar energy generation • PV-WT-BS HES can supply continues power to the island	[69]
	✓	✓			✓	✓	✓	✓		✓		SA	4 remote zones in India	Techno-economic and social	NPC, TAC, CRF, LCOE, JC and battery capacity	• The study investigated nine different combinations of HRES • MHP-BG-BM-WT-PV-BS HES found to be the best combination in terms of minimum NPC with highest JC	[74]
	✓	✓	✓					✓		✓		SA	City of Bizerte in Tunisia	Techno-economic and environmental	NPC, LCOE, excess energy and CO_2 emission	• WT-DG hybrid system found to be the most economical system in terms of NPC • PV-WT-BS-DG HES is better in terms of reliability	[155]
	✓	✓	✓	✓				✓	✓	✓	✓	SA	Tehran, Iran	Techno-economic	NPC, COE and		[84]

Table 4 (*continued*)

Software	Energy source							Energy storage		Energy conversion		SA/GC	Location	Analysis	Factors	Key points	Ref
	PV	WT	DG	FC	HG	BG	BM	BS	HT	CO	EL						
														and environment	emissions	• The PV-WT-BS HES is the third economical system in terms of NPC while WT-DG-BS-FC is the most economical • However, PV-WT-BS system provided the most environmental friendly system	
	✓	✓	✓							✓		SA	Timiaouine town, Algeria	Techno-economic and environment	NPC, COE and CO_2 emissions	• PV-WT-DG HES can supply a 100% of electricity demand of the town • CO_2 emissions reduced by 96%	[157]
iHOGA	✓	✓	✓					✓		✓		SA	Kampung Opar in Malaysia	Techno-economic and environment	NPC, COE and CO2 emission	• PV-WT-BS HES can be used to satisfy the load demand at rural areas in Malaysia without using DG	[68]
	✓	✓	✓					✓		✓		SA	Zaragoza, Spain	Economic and environmental	LCOE, LCE, CO2 emissions	• The study found that including DG will provide better LCE • PVP and WT reduces the hours of DG which reduce the emissions	[162]

while LPSP is used to assess the system's reliability. The authors studied the optimal hybrid PV, WT, and BS system to supply electricity for a building in Tehran, Iran. In addition, the authors examined the influence of the PV panel's tilt angle on size optimization. The optimal size combination is achieved with 0% LPSP and 3.28% payback time. The summary of hybrid techniques is presented in Table 3.

4.3. Optimization computer software tools

Many software tools have been used in optimization of renewable energy systems [148]. Recently, two software tools, namely, HOMER and iHOGA, have been mostly used for sizing a standalone PV-WT HES.

HOMER can optimize and simulate energy systems including renewable and conventional sources, as well as an energy storage system in standalone and grid-connected modes. Optimization can be conducted using previous meteorological data according to monthly averaged or hourly data based on the site location. HOMER Pro is the improved version of HOMER with some added features such as optimizer, multi-year module, advanced battery, load profile options, monthly demand limits, and ability to link with the Matlab software [149–151]. HOMER software is widely used for sizing a standalone hybrid PV and WT energy system and other energy sources and storage systems integrated with it [19,58,60,94,152]. The software is limited as it performs only a single-objective optimization by minimizing NPC and the input variables should be inserted by the user [35].

These software tools are used to find the optimal design of HES for different locations worldwide by considering the main objective function of minimizing NPC and subjecting it to numerous environmental, reliability, and social constraints. Table 4 provides the selected most recent studies from different locations worldwide.

Most studies found that PV-WT-BS energy resources is more feasible as it provide the lowest NPC and COE with low or zero CO_2 emissions when used in HRES [40,57]. Das et al. [61] performed a feasibility study to find the optimal size combination of HES for Kuakata, Bangladesh. The optimal size is achieved with a TNPC of $ 224,345 and zero emissions. A similar study by [40] found the optimal size of HES for a telecom load in Chennai, India. Seven combinations are examined to derive the most cost-effective, reliable, and less emission combination. The authors found that the PV-WT-BS system is the second most cost-effective system with zero emission. Fazelpour et al. [84] reported that PV-WT-BS system is the third most economical option in terms of minimum NPC with zero emission for a building in Tehran, Iran. A techno-economic study accomplished by [69] indicated that PV-WT-BS system can completely replace diesel generator and provide an economical and reliable energy system for a remote island in Hong Kong. Zahboune et al. [35] used HOMER Pro to determine the optimal size of a PV-WT-BS system for Oujda, Morocco and compared its results with the proposed MESCA method. The optimal combination by HOMER Pro has a TNPC of € 27,878.

The hybrid combination of a PV-WT-DG-BS system is widely considered for various locations. Mamaghani et al. [62] studied the optimal combinations for three different villages in Colombia. The authors found that the PV-WT-DG-BS system can provide an optimal cost-effective and reliable system with limited emissions for the Puerto Estrella village. Another study by [56] found the optimal mix of HES in terms of minimizing NPC, COE, and CO_2 emissions for the KLIA Sepang site in Malaysia. The authors compared the optimal HES with conventional plant and reported that the hybrid PV-WT-DG-BS system reduces NPC and GHG emissions compared with conventional plant. Baneshi and Hadianfard [78] carried out a techno-economic and environmental study for the same combination in Shiraz, Iran, wherein authors considered NPV, COE, RF, internal rate of return (IRR), and CO_2 emissions in their feasibility study. The PV-WT-DG-BS system is found to be optimal in terms of the optimal COE and RF with maximum reduction of CO_2 compared with other off-grid combination. Baghdadi et al. [153] conducted a techno-economic feasibility study for a PV-WT-DG-BS system for Adrar, Algeria. The authors used HOMER to find the optimal combination and then conducted a power management of the system by Matlab software. The optimal combination was able to provide high RF and 70% reduction in fossil fuel consumption. Another techno-economic study by [154] considered NPC, LCOE, and RF to determine the optimal renewable mix for six zones in Nigeria. The authors considered the tilt angle of PVP in their study to enhance PVP performance. A techno-economic, environmental study by [155] on HES for Bizerte, Tunisia reported that the PV-WT-DG-BS system is the most reliable with limited emissions, whereas the WT-DG system is the most cost-effective. A similar study by [156] found that the PV-WT-DG-BS system ensures a significant reduction in GHG and is cost-effective for a large resort in South China Sea in Malaysia. Bentouba and Bourouis [157] considered DG as a back-up source to PV and WT. The optimization results showed that PV-WT-DG HES can satisfy 100% of the load demand with a 96% reduction in carbon emissions.

A techno-economic study by [57] indicated that the PV-WT-FC-BS-HT system is the most cost-effective and reliable combination for the Bozcaada island in Turkey. Moreover, the authors concluded that the increase in annual average of solar radiation and wind speed decreases both NPC and COE. Another techno-economic study is conducted by [74] to investigate the best of nine different HRES combinations. The study showed that the hybrid MHP-BG-BM-WT-PV-BS system provides minimum NPC and maximum JC. A study by [85] found that HES with HG can be cost-effective and reliable with limited emissions for the Tioman Island in Malaysia.iHOGA is another software tool used in the size optimization of standalone PV-WT HES. iHOGA is a hybrid energy system optimization software developed by the electric engineering department of the University of Zaragoza [158]. The optimization can be conducted by using input data of component, economic, and constraints resources. The simulation is carried out for 1-h interval in which all system variables remain unchanged throughout the simulation. This software utilizes GA to perform the size optimization of single- or multi-objective optimization and optimal control strategies with less computational time compared to the use of GA alone. In addition, it utilizes Monte Carlo Simulation to perform probabilistic analysis [12,142]. It also can perform analysis for buy and sell for electric energy when the hybrid system is connected to the utility grid with different cases of net metering [25,159] and allows for selling the surplus hydrogen produced by the electrolyzer [158]. It allows to include the MPPT function in the PV charge regulator and estimate the lifetime of the lead-acid batteries [160] based on model predication of lead-acid batteries developed by [161]. In addition, it consider the efficiency of the inverter as a function of the power output. Moreover, it considers the height of the wind turbine, and atmospheric pressure and air density in the optimization problem [158]. In version 2.0 PRO plus, the social criteria that effects the optimization of HES such as HDI and JC can be included in the optimization problem. The optimization is achieved by minimizing NPC and additional variables can be minimized such as lifecycle emissions and unmet load. Fadaeenejad et al. [68] used the iHOGA software to examine the optimal size combination for a village in Malaysia in terms of minimizing the amount of CO_2 emission, NPC, and COE. The study showed that the hybrid PV-WT-BS energy system is a cost-effective and reliable option for villages in Malaysia. Dufo-Lopez et al. [162] used HOGA by utilizing two algorithms namely MOEA based on strength pareto evolutionary algorithm (SPEA) and SPEA2, and GA. MOEA algorithm is utilized to search for the optimal combinations of components in terms of minimizing costs and emissions while GA algorithm is used to find the optimal control strategy in terms with lowest cost. The authors performed four optimization cases for two locations in Spain namely Zaragoza and Jaca. The study found that the PV-WT-DG-BS system and PV-DG-BS system are the most economical and eco-friendly combination for Zaragoza and Jaca respectively.

4.4. Comparison between algorithms

The review demonstrates that many algorithms are applied for sizing the standalone hybrid PV-WT system coupled with different energy sources and storage systems. Table 5 summarizes the studies conducted in comparing the algorithms used in the size optimization of HES.

PSO is considered as one of the most used algorithm in HES size optimization due to its good performance, flexibility, and simplicity. However, PSO has a low performance in solving non-coordinate system as it defines the particle basis (RES components) based on three-dimensional coordinates (x, y, z) only. This limitation makes the optimization results insufficient when the system consists of more than three components. Moreover, in some cases, PSO tends to converge to a local optimal solution [18]. To overcome these drawbacks, Zhou and Sun [73] proposed SAPSO. The advantages of SAPSO over conventional PSO include its ability to avoid the trapping at local optimal values and improve the diversity of PSO to solve the non-coordinate system and improve the global searching by reducing computational time. MBA is used to optimize the size of HES and is compared with PSO, CS, and ABC. This study again proved that PSO cannot provide the most optimal solution due to its low performance in non-coordinate problems. Moreover, ABC is compared to PSO and HOMER, which showed that ABC has better computational time, and better results compared with that of PSO [17]. Additionally, the study found that CS has better quality results followed by ABC. In the other hand, MBA can achieve the best optimal result compared to PSO, CS, and ABC with less computational time, as well as the lowest mean and standard deviation [53]. PSO can be improved in terms of computational time and convergence of results. A study by [51] proposed MPSO to find the optimal renewable mix with minimum investment cost. MPSO provided faster convergence and shorter computational time than conventional PSO.

SA is a generic probabilistic algorithm and is a good option for the global optimization problem. However, this method is not widely used in standalone HES size optimization because of the low precision of its solutions compared to other algorithms such as PSO, GA and FPA [18,41,147]. A discrete version of SA (DSA) is compared with DHS to evaluate its performance in sizing HES. Unlike DHS, DSA failed to determine the optimal solutions [138]. By taking the advantage of SA in avoiding trapping at the local minima, SA can be successfully used in HES size optimization by combining it with search algorithm. DCHSSA is a combination of SA and two search algorithms, namely, CS and HS. DCHSSA provided more precise results and is the best optimal combination of HES compared with DSA and DHSSA [144]. Another study [147] combined SA with FPA to form a hybrid FPA-SA algorithm and compared it with PSO and GA. FPA-SA is found to have better-quality results with less computational time compared to GA and precise optimal values compared to PSO.

Compared to other iterative procedures, TS is an iterative optimization method that can avoid trapping in the local solutions. However, TS needs to start from the feasible solution and requires a large number of performed simulations. In [87], the authors found that combining TS with SA overcomes this drawback. The initial feasible solution can be obtained by SA and fed to TS. There-

Table 5
Comparison of size optimization methods.

Proposed method	Compared methods	System components	Objective function	The performance of proposed method compared with other methods	Ref.
Mine blast algorithms (MBA)	PSO, cuckoo search (CS) and artificial bee colony (ABC)	PV-WT-FC	Minimize ATC	• MBA provides the minimal annual cost compared to the other algorithms • Less computational time	[53]
Hybrid big bang–big crunch (HBB-BC)	PSO and discrete harmony search (DHS)	PV-WT-BS	Minimize TPC	• Higher optimal solutions accuracy • Smaller standard deviation (Std.) compared to other algorithms	[54]
Hybrid GA and exhaustive search technique	GA	PV-WT-BS	Minimize total cost	• Provides same optimal solution but with smaller number of iterations than GA	[36]
Ant colony optimization (ACO)	GA and ABC	PV-WT-BS	Minimize total cost	• ACO, GA and ABC provided same optimal costs • ACO is faster by providing lower optimal convergence iterations and optimal convergence time	[135]
Hybrid SA-Tabu search	SA and TA	PV-WT-BS - DG-FC	Minimize COE	• Higher quality of solutions • Faster convergence	[87]
PSO, TS and SA	Improved PSO(IPSO), improved harmony search (HIS), improved harmony search-based simulated annealing (IHSBSA) and artificial bee swarm optimization (ABSO)	PV-WT-BS	Minimize total annual cost (TAC)	• At $LPSP_{max} = 2\%$, the algorithms ranked based on mean, standard deviation, worst and best indexes. The indexes have been reported over 50 runs • ABSO ranked as 1 as it yields better results than the other algorithms • IHSBSA, HIS, IPSO, PSO, TS and SA ranked as 2,3,4,5,6 and 7 respectively	[67]
Artificial bee colony (ABC)	PSO and HOMER	PV-WT-BM-BS	Minimize TC	• ABC provided slightly better convergence rate compared to PSO by converging in almost 10th iteration • ABC provided faster computational time with better quality results in terms of minimizing LCOE	[17]
Cuckoo search (CS)	PSO and GA	PV-WT-BS	Minimize total cost	• CS faster in optimization as it reduces the computation burden • CS sample the search space more efficiently and generated new solutions which provided better solutions quality compared to GA and PSO	[49]
Natural selection particle swarm optimization (NSPSO)	GA	PV-WT-BS	LPSP, LCC, LEP and K_l	• NSPSO avoids a premature convergence effectively • It provides precise results with lower fitness function value	[42]
Enumeration-based iterative	HOMER	PV-WT-DG-BS	Minimize LCC	• The proposed algorithm provided lower LCC	[47]
Markov based GA	Chronology-based GA	PV-WT-DG	Minimize total cost	• Markov based GA has much smaller CPU time • Markov based GA provided better cost	[143]
Discrete harmony search (DHS)	Discrete simulated annealing (DSA)	PV-WT-DG-BS	Minimize TAC	• DHS provided better results with less run time than DSA	[138]
Discrete chaotic harmony search-based simulated annealing algorithm (DCHSSA)	Discrete simulated annealing (DSA) and Discrete harmony search-based simulated annealing (DHSSA)	PV-WT-BS	Minimize TAC	• DCHSSA yields better results in terms of mean and worst values than other algorithms • DCHSSA provided same ATC results as DHSSA	[144]
Harmony search-based chaotic search (HSBCS)	Harmony search (HS)	PV-WT-BS-RO	Minimize LCC	• It provides better average index than HS • It provides better standard deviation and mean simulation time than HS	[145]
Simulated annealing particle swarm optimization (SAPSO)	PSO	PV-WT-BS-SC	Minimize total cost	• SAPSO yields better cost results in less computation time	[73]
Modified particle awarm optimization (MPSO)	PSO	PV-WT-BS	Minimize TIC	• MPSO gives fast result convergence and shorter computational time	[51]
Hybrid flower pollination algorithm simulated annealing (FPA/SA)	GA and PSO	PV-WT-BS	Minimize LPSP and maximize cumulative savings	• FPA/SA provided better results quality than GA • FPA/SA had a precise optimum values than PSO • FPA/SA has better performance as it has less convergence time	[147]
PSO	Differential evolution (DE)	PV-WT-FC-HT	Minimize TC	• PSO has lower number of epoch • PSO converging faster than DE	[75]
Modified electric system cascade analysis (MESCA)	HOMER pro	PV-WT-BS	Minimize TAC	• MESCA less iterations with slightly less computational time than HOMER pro • MESCA provides more flexibility in selection of sources of energy types	[35]
Hybrid teaching-learning-based optimization algorithm (TLBO)	GA and PSO	PV-WT-BS-DG	Minimize TAC, LPSP, and fuel cost	• Hybrid TLBO provided better quality results (better total cost)	[38]

fore, the use of such hybrid algorithm provides better-quality HES optimal size results compared to the use of TS or SA alone. In [67], the authors examined the performance of seven heuristic algorithms in terms of minimizing the TAC of different hybrid system combinations. The algorithms are ranked based on mean, standard deviation, and worst and best indexes of over 50 runs, and ABSO was found to provide better results than IHSBSA, IHS, IPSO, PSO, TS, and SA in terms of minimizing the TAC.

GA can provide good convergence by avoiding trapping in local optimal solutions; however, it requires a large number of iterations, which increase response time [18]. To overcome this drawback, GA can be combined with an exhaustive-search method to take the advantage of GA as it can converge to a much wider search space and avoid trapping in local solution and the advantage of exhaustive-search technique to rapidly and effectively find the optimal solution within the search space [36]. Additionally, GA required long computational time as each iteration includes a set of numerous solutions. To overcome this, a stochastic model such as Markov or chronology can be used to predict the future state based on its current state only to reduce computational time and provide better results. In [143], a comparison between the Markov- and chronology-based GA in optimizing HES indicated that the former can reduce the CPU time more than the latter and provide the most feasible solution. GA has high performance in the search process, which can be combined with PSO to deal with defects of both PSO and GA by improving the precision of the results and the global optimization ability [42].

CS-based optimization methodology is efficient in finding the optimal solutions for complex problems compared to PSO and GA as it has faster computational time. Additionally, CS-based optimization methodology provides better quality results as it samples the search space more efficiently and, therefore, can be utilized to solve complex HES sizing problem and provide efficient optimal solutions [49]. ACO was compared with GA and ABC to minimize the total cost of a hybrid PV-wind battery system. The optimal cost results from all algorithms are the same. However, ACO provided the optimal solutions with less convergence iterations and faster convergence time [135].

DHS and PSO can avoid trapping at the local optimum value and continue the search for global values. However, in very complex systems, they perform with relatively high computation time and low convergence. In this context, HBB-BC can avoid trapping at local optimum values, same as DHS and PSO, and can provide faster convergence with less computational time [54].

The initial population input data of the optimization algorithms are unbounded and diverged due to random nature of renewable sources (solar radiation, wind speed, and etc.). Hence, the optimization results may be far from the minimum global solutions. In [75], the authors examined the difference between PSO and DE algorithms in the HES size optimization. PSO provided better solutions in terms of convergence to global best values and convergence speed when compared to DE. When random initial conditions are chosen for PSO and DE algorithms, DE failed to provide global convergence as initial conditions are far away from the minimum global solution, whereas PSO yielded the optimal solutions close to minimum global solutions. Therefore, the use of PSO for HES size optimization when unbounded random initial conditions are applied is highly recommended, whereas DE can better perform when initial conditions are bounded to values near the global best value [163] and can be used along with other algorithms to compensate its population diversity decay in order to avoid suboptimal trap.

Hybrid TLBO is the combination of a search algorithm TLBO and a selection algorithm clonal selection algorithm. Hybrid TLBO uses a fewer number of parameters compared to GA and PSO but with better performance. This algorithm can provide a better-quality set of optimal solutions but might take longer computational time. However, hybrid TLBO can be considered as a good choice for HES size optimization as it has superior performance in dealing with the fluctuation of solar irradiation and wind speed data [38].

MESCA can provide almost a similar quality of optimization results compared to HOMER with less computational time as it performs the optimization with less iterations. Therefore, MESCA is recommended for HES optimization in complex sites [35]. HOMER software takes longer time to simulate HES and obtains the results compared to other artificial algorithms such as ABC and PSO [17]. In another study [47], authors proposed enumeration-based iterative algorithm and compared it with HOMER to evaluate its performance in sizing HES. The study found that HOMER provided a high value of renewable energy penetration because it does not dump the excess energy generated from RES. Therefore, the proposed iterative method can yield better optimal results in terms of minimizing LCC.

5. Critical findings and discussions

- The implementation of HRESs provides a cost-effective and reliable option, given the fuel supply shortage and high cost associated with grid extension for islands and remote rural areas. The selection of RESs for a specific location is based on site specifications. This review shows that the most preferable hybrid energy system for islands and remote areas is the PV-WT-DG-BS system as it provides reliability and ensures continuity of power supply, followed by PV-WT-BS as it is the most eco-friendly combination with zero emissions as shown in Fig. 4.

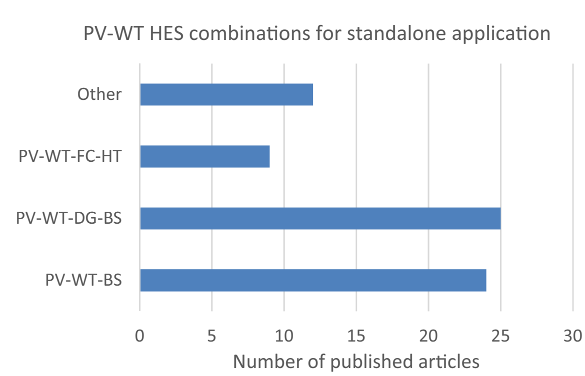

Fig. 4. PV-WT HES combinations for standalone application since 2012–2016.

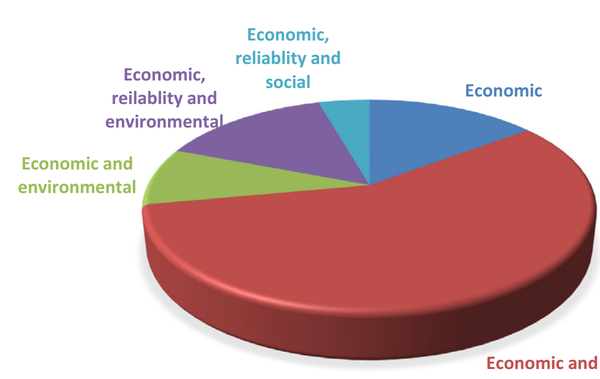

Fig. 5. Assessment parameters used for standalone PV-WT HES since 2012.

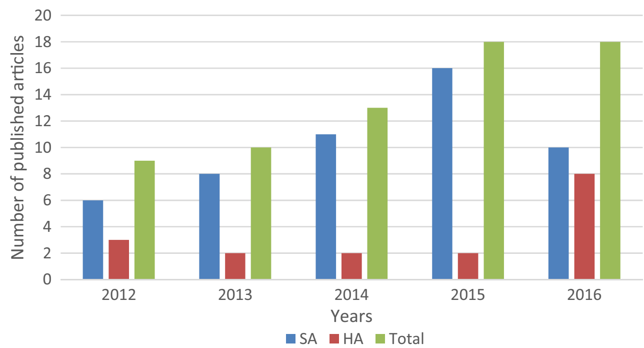

Fig. 6. Use of single and hybrid algorithms for sizing of standalone PV-WT HES from 2012 to 2016.

- As most standalone hybrid energy systems are used for remote and rural areas, in many cases, the load profile data are unavailable. Moreover, the accuracy of load profile immensely influences the size optimization results. Therefore, more research is required in the field of load profile estimation and forecasting to establish and construct more accurate predictions for the load profile. The new technique should not only focus on the variables of technical and climate specifications in forecasting process but also include social factors.
- The peaks of solar irradiation and wind speed influence the size optimization solutions. Therefore, usage of hourly annual solar and wind data rather than daily or monthly data is recommended as hourly data contain the troughs and peaks of solar irradiation and wind speed.
- Based on the reviewed studies, the manufacturing costs of hybrid system components are the main reason of the high initial costs of HES, which require a significant reduction to lessen initial system cost. This reduction will decrease payback time and increase return in investment which will eventually increase social acceptance and human development index.
- As shown in Fig. 5, few studies have considered social assessments such as human development, job creation, and social acceptance in optimization problems. These social factors are usually affected by the total cost and energy savings of HES, which influence HES sizing optimization. Therefore, considering these factors in size optimization problems is recommended.
- PV, wind, and battery system have high potential in off-grid application, thus, improvements in the life cycle of batteries and the efficiency of power converters can increase the use of this combination due to its zero-emission advantage.
- Considering the tilt angle of the PV array as a constraint in the size optimization problem is important as it affects the accuracy of the optimal results.
- The height of WT and its swept area are found be having a significant effect on the optimization results. In this context, these constraints in the optimization problem should be considered.
- From the review, it is found that most researchers look into the cost and then the reliability objective in optimization as shown in Fig. 5. Less researchers considered the environmental objective function. Cost and reliability are the criteria given the most concern in the hybrid system. However, environmental objective especially when the hybrid system contains conventional energy source should be given increased attention.
- As can be noticed from this review, the use of classical size optimization methods recently declined, and a growing trend is observed toward the use of modern size optimization methods as they provide a set of optimal results that allow decision-makers to select the best suitable combination of HES. Therefore, the use of modern methods in HES is recommended as they can provide promising and realistic optimal sizes.
- Owing to the stochastic nature and the capability of artificial algorithms in solving multi-objective, non-linear, and complex optimization problems, these methods have attracted much attention as the usage of artificial methods in HES size optimization drew more attention than the classical methods.
- SA algorithm is not widely used in HES size optimization. However, SA can escape from trapping at local solutions. Therefore, SA is best used when it is combined with other evolutionary algorithms and/or search algorithms to improve the accuracy of its optimal solutions and enhance the global search.
- PSO has been widely used in sizing HES. However, conventional PSO suffers from premature convergence. Therefore, in current studies, the use of conventional PSO alone in size optimization of HES started to decline. As a result, the use of PSO variant and improved versions of PSO is currently utilized by many studies as these improved versions provide better results compared to conventional PSO.
- As the hybrid energy system optimization considered a complex problem, many objective functions and constraints should be considered to improve quality results. Numerous studies currently use triple-objective optimization problems as these provide more realistic solutions and, hence, more accurate optimal results.
- The most common optimization method implemented for triple-objective problems is NSGA-II. NSGA-II and its variant (such as controlled elitist genetic algorithm) provided good performance in solving triple-objective optimization problem. Additionally, PICEA demonstrated good performance in solving multi-objective functions. Therefore, the use of this algorithm in HES size optimization problem is recommended.
- Single algorithms using artificial methods provide good performance in solving size optimization problem of HES, whereas hybrid algorithms perform better with more promising results. In this context, the use of hybrid algorithms recently extensively increased in size optimization for standalone PV-WT HES as shown in Fig. 6.
- As can be seen from this review, newly developed hybrid algorithms such as TLBO, FPA/SA, and NSPSO provide better-quality results with less computational time compared with GA and PSO.

6. Conclusion

This paper presents a comprehensive review and critical comparison of most recent size optimization methods of standalone solar and wind based hybrid energy systems. The most popular hybrid combination for islands and remote rural areas found to be the solar, wind, diesel generator, and battery storage based hybrid energy system as it provides more reliable and continuous power supply. Finding the optimum size of each element is a key factor to reduce the cost while maintaining the reliability and social acceptance.

In order to solve a sizing optimization problem of a standalone solar and wind hybrid energy system, various assessment parameters such as economical, reliability, environmental and social parameters are explained and summarized. The selection of some of these parameters is essentially to obtain an optimal combination for the standalone solar and wind system. Moreover, the metrological data and load profile have an impact on the size optimization problem. Based on the review, it is observed that the use of forecasted solar, wind, and load profile data in the optimization problem improve the size optimization results compared to the use of historical data.

Most of the papers for sizing a standalone solar and wind hybrid system are carried out based on single algorithms including classical and artificial methods. Artificial methods using single algorithms has the ability to search for local and global optima and provide a set of optimal results with less computational time. Therefore, artificial methods have attracted much attention in sizing of standalone solar and wind system than classical methods. However, as a standalone solar and wind systems are rapidly growing especially for islands and remote areas, there is a need for even much accurate and highly advanced optimization approaches. Therefore, hybrid algorithms have recently been extensively applied for the sizing optimization of standalone solar and wind hybrid system. Moreover, software computer tools are also used widely for sizing and designing of standalone solar and wind system. However, using modern methods such as artificial algorithms and hybrid algorithms provide more accurate optimization results than software tools as they have the ability to solve multi-objective optimization problems.

References

[1] Initiative GE. Global electricity initiative executive summary 2014. GEI2014.
[2] Kuang Y, Zhang Y, Zhou B, Li C, Cao Y, Li L, et al. A review of renewable energy utilization in islands. Renew Sustain Energy Rev 2016;59:504–13.
[3] Sinha S, Chandel SS. Review of recent trends in optimization techniques for solar photovoltaic–wind based hybrid energy systems. Renew Sustain Energy Rev 2015;50:755–69.
[4] Van TV, Norton M, Ivanov C, Delimar M, Hatziargyriou N, Stromsather J, et al. Organic growth: toward a holistic approach to European research and innovation. IEEE Power Energy Mag 2015;13:30–7.
[5] "Monitoring report 2015". Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen; 2016.
[6] Kroposki B, Mather B. Rise of distributed power integrating solar energy into the grid. IEEE Power Energy Mag 2015;13:14–8.
[7] Cheng M, Zhu Y. The state of the art of wind energy conversion systems and technologies: a review. Energy Convers Manage 2014;88:332–47.
[8] Khare V, Nema S, Baredar P. Solar–wind hybrid renewable energy system: a review. Renew Sustain Energy Rev 2016;58:23–33.
[9] Zhang D, Evangelisti S, Lettieri P, Papageorgiou LG. Economic and environmental scheduling of smart homes with microgrid: DER operation and electrical tasks. Energy Convers Manage 2016;110:113–24.
[10] Koohi-Kamali S, Rahim NA. Coordinated control of smart microgrid during and after islanding operation to prevent under frequency load shedding using energy storage system. Energy Convers Manage 2016;127:623–46.
[11] Camblong H, Baudoin S, Vechiu I, Etxeberria A. Design of a SOFC/GT/SCs hybrid power system to supply a rural isolated microgrid. Energy Convers Manage 2016;117:12–20.
[12] Chauhan A, Saini RP. A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control. Renew Sustain Energy Rev 2014;38:99–120.
[13] Mannke F, Mohee R, Schulte V, Surroop D. Climate-smart technologies-integrating renewable energy and energy efficiency in mitigation and adaptation responses. Berlin/Heidelberg; 2013.
[14] Blechinger P, Cader C, Bertheau P, Huyskens H, Seguin R, Breyer C. Global analysis of the techno-economic potential of renewable energy hybrid systems on small islands. Energy Policy 2016;98:674–87.
[15] Shirley R, Kammen D. Renewable energy sector development in the Caribbean: Current trends and lessons from history. Energy Policy 2013;57:244–52.
[16] Petrakopoulou F. On the economics of stand-alone renewable hybrid power plants in remote regions. Energy Convers Manage 2016;118:63–74.
[17] Singh S, Singh M, Kaushik SC. Feasibility study of an islanded microgrid in rural area consisting of PV, wind, biomass and battery energy storage system. Energy Convers Manage 2016;128:178–90.
[18] Zahraee SM, Khalaji Assadi M, Saidur R. Application of artificial intelligence methods for hybrid energy system optimization. Renew Sustain Energy Rev 2016;66:617–30.
[19] Ramli MAM, Hiendro A, Al-Turki YA. Techno-economic energy analysis of wind/solar hybrid system: Case study for western coastal area of Saudi Arabia. Renewable Energy 2016;91:374–85.
[20] Siddaiah R, Saini RP. A review on planning, configurations, modeling and optimization techniques of hybrid renewable energy systems for off grid applications. Renew Sustain Energy Rev 2016;58:376–96.
[21] Dufo-López R, Cristóbal-Monreal IR, Yusta JM. Optimisation of PV-wind-diesel-battery stand-alone systems to minimise cost and maximise human development index and job creation. Renewable Energy 2016;94:280–93.
[22] Ribeiro AED, Arouca MC, Coelho DM. Electric energy generation from small-scale solar and wind power in Brazil: The influence of location, area and shape. Renewable Energy 2016;85:554–63.
[23] Mahesh A, Sandhu KS. Hybrid wind/photovoltaic energy system developments: Critical review and findings. Renew Sustain Energy Rev 2015;52:1135–47.
[24] Al Busaidi AS, Kazem HA, Al-Badi AH, Farooq Khan M. A review of optimum sizing of hybrid PV–Wind renewable energy systems in oman. Renew Sustain Energy Rev 2016;53:185–93.
[25] Upadhyay S, Sharma MP. A review on configurations, control and sizing methodologies of hybrid energy systems. Renew Sustain Energy Rev 2014;38:47–63.
[26] Olatomiwa L, Mekhilef S, Huda ASN, Ohunakin OS. Economic evaluation of hybrid energy systems for rural electrification in six geo-political zones of Nigeria. Renewable Energy 2015;83:435–46.
[27] Zhou W, Lou C, Li Z, Lu L, Yang H. Current status of research on optimum sizing of stand-alone hybrid solar–wind power generation systems. Appl Energy 2010;87:380–9.
[28] Fathima AH, Palanisamy K. Optimization in microgrids with hybrid energy systems – A review. Renew Sustain Energy Rev 2015;45:431–46.
[29] Shivarama Krishna K, Sathish Kumar K. A review on hybrid renewable energy systems. Renew Sustain Energy Rev 2015;52:907–16.
[30] Askarzadeh A. Optimisation of solar and wind energy systems: a survey. Int J Ambient Energy 2016:1–10.
[31] Erdinc O, Uzunoglu M. Optimum design of hybrid renewable energy systems: Overview of different approaches. Renew Sustain Energy Rev 2012;16:1412–25.
[32] Fadaee M, Radzi MAM. Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review. Renew Sustain Energy Rev 2012;16:3364–9.
[33] Luna-Rubio R, Trejo-Perea M, Vargas-Vázquez D, Ríos-Moreno GJ. Optimal sizing of renewable hybrids energy systems: A review of methodologies. Sol Energy 2012;86:1077–88.
[34] Bourennani F, Rahnamayan S, Naterer GF. Optimal design methods for hybrid renewable energy systems. Int J Green Energy 2014;12:148–59.
[35] Zahboune H, Zouggar S, Krajacic G, Varbanov PS, Elhafyani M, Ziani E. Optimal hybrid renewable energy design in autonomous system using Modified Electric System Cascade Analysis and Homer software. Energy Convers Manage 2016;126:909–22.
[36] Tito SR, Lie TT, Anderson TN. Optimal sizing of a wind-photovoltaic-battery hybrid renewable energy system considering socio-demographic factors. Sol Energy 2016;136:525–32.
[37] Kamjoo A, Maheri A, Dizqah AM, Putrus GA. Multi-objective design under uncertainties of hybrid renewable energy system using NSGA-II and chance constrained programming. Int J Electr Power Energy Syst 2016;74:187–94.
[38] Cho J-H, Chun M-G, Hong W-P. Structure optimization of stand-alone renewable power systems based on multi object function. Energies 2016;9:649.
[39] Baghaee HR, Mirsalim M, Gharehpetian GB, Talebi HA. Reliability/cost-based multi-objective Pareto optimal design of stand-alone wind/PV/FC generation microgrid system. Energy 2016;115:1022–41.
[40] Margaret Amutha W, Rajini V. Techno-economic evaluation of various hybrid power systems for rural telecom. Renew Sustain Energy Rev 2015;43:553–61.
[41] Maleki A, Ameri M, Keynia F. Scrutiny of multifarious particle swarm optimization for finding the optimal size of a PV/wind/battery hybrid system. Renewable Energy 2015;80:552–63.
[42] Ma G, Xu G, Chen Y, Ju R. Multi-objective optimal configuration method for a standalone wind-solar-battery hybrid power system. IET Renew Power Gener 2016.
[43] Maleki A, Khajeh MG, Ameri M. Optimal sizing of a grid independent hybrid renewable energy system incorporating resource uncertainty, and load uncertainty. Int J Electr Power Energy Syst 2016;83:514–24.
[44] Nehrir MH, Wang C, Strunz K, Aki H, Ramakumar R, Bing J, et al. A review of hybrid renewable/alternative energy systems for electric power generation: configurations, control, and applications. IEEE Trans Sustain Energy 2011;2:392–403.
[45] Malheiro A, Castro PM, Lima RM, Estanqueiro A. Integrated sizing and scheduling of wind/PV/diesel/battery isolated systems. Renewable Energy 2015;83:646–57.
[46] Gan LK, Shek JKH, Mueller MA. Hybrid wind–photovoltaic–diesel–battery system sizing tool development using empirical approach, life-cycle cost and performance analysis: A case study in Scotland. Energy Convers Manage 2015;106:479–94.
[47] Bhuiyan FA, Yazdani A, Primak SL. Optimal sizing approach for islanded microgrids. IET Renew Power Gener 2015;9:166–75.
[48] Zhao B, Zhang X, Li P, Wang K, Xue M, Wang C. Optimal sizing, operating strategy and operational experience of a stand-alone microgrid on Dongfushan Island. Appl Energy 2014;113:1656–66.
[49] Sanajaoba S, Fernandez E. Maiden application of Cuckoo Search algorithm for optimal sizing of a remote hybrid renewable energy System. Renewable Energy 2016;96:1–10.
[50] Hosseinalizadeh R, Shakouri H, Mohsen G, Amalnick S, Taghipour P. Economic sizing of a hybrid (PV–WT–FC) renewable energy system (HRES) for stand-alone usages by an optimization-simulation model: Case study of Iran. Renew Sustain Energy Rev 2016;54:139–50.
[51] Hassan A, Kandil M, Saadawi M, Saeed M. Modified particle swarm optimisation technique for optimal design of small renewable energy system supplying a specific load at Mansoura University. IET Renew Power Gener 2015;9:474–83.
[52] Gharavi H, Ardehali MM, Ghanbari-Tichi S. Imperial competitive algorithm optimization of fuzzy multi-objective design of a hybrid green power system

with considerations for economics, reliability, and environmental emissions. Renewable Energy 2015;78:427–37.
[53] Fathy A. A reliable methodology based on mine blast optimization algorithm for optimal sizing of hybrid PV-wind-FC system for remote area in Egypt. Renewable Energy 2016;95:367–80.
[54] Ahmadi S, Abdi S. Application of the Hybrid Big Bang-Big Crunch algorithm for optimal sizing of a stand-alone hybrid PV/wind/battery system. Sol Energy 2016;134:366–74.
[55] Ogunjuyigbe ASO, Ayodele TR, Akinola OA. Optimal allocation and sizing of PV/Wind/Split-diesel/Battery hybrid energy system for minimizing life cycle cost, carbon emission and dump energy of remote residential building. Appl Energy 2016;171:153–71.
[56] Shezan SA, Julai S, Kibria MA, Ullah KR, Saidur R, Chong WT, et al. Performance analysis of an off-grid wind-PV (photovoltaic)-diesel-battery hybrid energy system feasible for remote areas. J Clean Prod 2016;125:121–32.
[57] Kalinci Y, Hepbasli A, Dincer I. Techno-economic analysis of a stand-alone hybrid renewable energy system with hydrogen production and storage options. Int J Hydrogen Energy 2015;40:7652–64.
[58] Adaramola MS, Agelin-Chaab M, Paul SS. Analysis of hybrid energy systems for application in southern Ghana. Energy Convers Manage 2014;88:284–95.
[59] Celik AN. Optimisation and techno-economic analysis of autonomous photovoltaic–wind hybrid energy systems in comparison to single photovoltaic and wind systems. Energy Convers Manage 2002;43:2453–68.
[60] Bhattacharjee S, Acharya S. PV–wind hybrid power option for a low wind topography. Energy Convers Manage 2015;89:942–54.
[61] Das HS, Dey A, Wei TC, Yatim AHM. Feasibility analysis of standalone PV/wind/battery hybrid energy system for Rural Bangladesh. Int J Renew Energy Res 2016;6:403–12.
[62] Haghighat Mamaghani A, Avella Escandon SA, Najafi B, Shirazi A, Rinaldi F. Techno-economic feasibility of photovoltaic, wind, diesel and hybrid electrification systems for off-grid rural electrification in Colombia. Renewable Energy 2016;97:293–305.
[63] Nandi SK, Ghosh HR. Prospect of wind–PV-battery hybrid power system as an alternative to grid extension in Bangladesh. Energy 2010;35:3040–7.
[64] Ahadi A, Kang S-K, Lee J-H. A novel approach for optimal combinations of wind, PV, and energy storage system in diesel-free isolated communities. Appl Energy 2016;170:101–15.
[65] Derakhshan G, Shayanfar HA, Kazemi A. Optimal design of solar PV-WT-SB based smart microgrid using NSHCSO. Int J Hydrogen Energy 2016.
[66] Askarzadeh A, dos Santos Coelho L. A novel framework for optimization of a grid independent hybrid renewable energy system: A case study of Iran. Sol Energy 2015;112:383–96.
[67] Maleki A, Pourfayaz F. Optimal sizing of autonomous hybrid photovoltaic/wind/battery power system with LPSP technology by using evolutionary algorithms. Sol Energy 2015;115:471–83.
[68] Fadaeenejad M, Radzi MAM, AbKadir MZA, Hizam H. Assessment of hybrid renewable power sources for rural electrification in Malaysia. Renew Sustain Energy Rev 2014;30:299–305.
[69] Ma T, Yang H, Lu L. A feasibility study of a stand-alone hybrid solar–wind–battery system for a remote island. Appl Energy 2014;121:149–58.
[70] Maleki A, Askarzadeh A. Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system. Int J Hydrogen Energy 2014;39:9973–84.
[71] Maleki A, Askarzadeh A. Artificial bee swarm optimization for optimum sizing of a stand-alone PV/WT/FC hybrid system considering LPSP concept. Sol Energy 2014;107:227–35.
[72] Ma T, Yang H, Lu L, Peng J. Technical feasibility study on a standalone hybrid solar-wind system with pumped hydro storage for a remote island in Hong Kong. Renewable Energy 2014;69:7–15.
[73] Zhou T, Sun W. Optimization of battery-supercapacitor hybrid energy storage station in wind/solar generation system. IEEE Trans Sustain Energy 2014;5:408–15.
[74] Chauhan A, Saini RP. Techno-economic feasibility study on Integrated Renewable Energy System for an isolated community of India. Renew Sustain Energy Rev 2016;59:388–405.
[75] Sanchez VM, Chavez-Ramirez AU, Duron-Torres SM, Hernandez J, Arriaga LG, Ramirez JM. Techno-economical optimization based on swarm intelligence algorithm for a stand-alone wind-photovoltaic-hydrogen power system at south-east region of Mexico. Int J Hydrogen Energy 2014;39:16646–55.
[76] Smaoui M, Abdelkafi A, Krichen L. Optimal sizing of stand-alone photovoltaic/wind/hydrogen hybrid system supplying a desalination unit. Sol Energy 2015;120:263–76.
[77] Rajanna S, Saini RP. Development of optimal integrated renewable energy model with battery storage for a remote Indian area. Energy 2016;111:803–17.
[78] Baneshi M, Hadianfard F. Techno-economic feasibility of hybrid diesel/PV/wind/battery electricity generation systems for non-residential large electricity consumers under southern Iran climate conditions. Energy Convers Manage 2016;127:233–44.
[79] Belfkira R, Zhang L, Barakat G. Optimal sizing study of hybrid wind/PV/diesel power generation unit. Sol Energy 2011;85:100–10.
[80] Shi B, Wu W, Yan L. Size optimization of stand-alone PV/wind/diesel hybrid power generation systems. J Taiwan Instit Chem Eng 2016.
[81] Suhane P, Rangnekar S, Khare A, Mittal A. Sizing and performance analysis of standalone wind-photovoltaic based hybrid energy system using ant colony optimisation. IET Renew Power Gener 2016;10:964–72.
[82] Zhao J, Yuan X. Multi-objective optimization of stand-alone hybrid PV-wind-diesel-battery system using improved fruit fly optimization algorithm. Soft Comput 2015;20:2841–53.
[83] Shi Z, Wang R, Zhang T. Multi-objective optimal design of hybrid renewable energy systems using preference-inspired coevolutionary approach. Sol Energy 2015;118:96–106.
[84] Fazelpour F, Soltani N, Rosen MA. Economic analysis of standalone hybrid energy systems for application in Tehran, Iran. Int J Hydrogen Energy 2016;41:7732–43.
[85] Khan MRB, Jidin R, Pasupuleti J, Shaaya SA. Optimal combination of solar, wind, micro-hydro and diesel systems based on actual seasonal load profiles for a resort island in the South China Sea. Energy 2015;82:80–97.
[86] Bekele G, Tadesse G. Feasibility study of small Hydro/PV/Wind hybrid system for off-grid rural electrification in Ethiopia. Appl Energy 2012;97: 5–15.
[87] Katsigiannis YA, Georgilakis PS, Karapidakis ES. Hybrid Simulated Annealing-Tabu Search Method For Optimal Sizing Of Autonomous Power Systems With Renewables. IEEE Trans Sustain Energy 2012;3.
[88] Chmiel Z, Bhattacharyya SC. Analysis of off-grid electricity system at Isle of Eigg (Scotland): Lessons for developing countries. Renewable Energy 2015;81:578–88.
[89] Sen R, Bhattacharyya SC. Off-grid electricity generation with renewable energy technologies in India: An application of HOMER. Renewable Energy 2014;62:388–98.
[90] Gupta RA, Kumar R, Bansal AK. BBO-based small autonomous hybrid power system optimization incorporating wind speed and solar radiation forecasting. Renew Sustain Energy Rev 2015;41:1366–75.
[91] Khatib T, Ibrahim IA, Mohamed A. A review on sizing methodologies of photovoltaic array and storage battery in a standalone photovoltaic system. Energy Convers Manage 2016;120:430–48.
[92] Louie H. Operational analysis of hybrid solar/wind microgrids using measured data. Energy Sustain Dev 2016;31:108–17.
[93] Hocaoglu FO, Gerek ON, Kurban M. The effect of model generated solar radiation data usage in hybrid (wind–PV) sizing studies. Energy Convers Manage 2009;50:2956–63.
[94] Sinha S, Chandel SS. Prospects of solar photovoltaic–micro-wind based hybrid power systems in western Himalayan state of Himachal Pradesh in India. Energy Convers Manage 2015;105:1340–51.
[95] Rajkumar RK, Ramachandaramurthy VK, Yong BL, Chia DB. Techno-economical optimization of hybrid pv/wind/battery system using Neuro-Fuzzy. Energy 2011;36:5148–53.
[96] Nogueira CEC, Vidotto ML, Niedzialkoski RK, de Souza SNM, Chaves LI, Edwiges T, et al. Sizing and simulation of a photovoltaic-wind energy system using batteries, applied for a small rural property located in the south of Brazil. Renew Sustain Energy Rev 2014;29:151–7.
[97] Khatod DK, Pant V, Sharma J. Analytical approach for well-being assessment of small autonomous power systems with solar and wind energy sources. IEEE Trans Energy Convers 2010;25:535–45.
[98] Ekren O, Ekren BY. Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing. Appl Energy 2010;87:592–8.
[99] Azimi R, Ghayekhloo M, Ghofrani M. A hybrid method based on a new clustering technique and multilayer perceptron neural networks for hourly solar radiation forecasting. Energy Convers Manage 2016;118:331–44.
[100] Chen H-C. Optimum capacity determination of stand-alone hybrid generation system considering cost and reliability. Appl Energy 2013;103:155–64.
[101] Vasilj J, Sarajcev P, Jakus D. Estimating future balancing power requirements in wind–PV power system. Renewable Energy 2016;99:369–78.
[102] Santana ÁL, Conde GB, Rego LP, Rocha CA, Cardoso DL, Costa JCW, et al. PREDICT – Decision support system for load forecasting and inference: A new undertaking for Brazilian power suppliers. Int J Electr Power Energy Syst 2012;38:33–45.
[103] Borunda M, Jaramillo OA, Reyes A, Ibargüengoytia PH. Bayesian networks in renewable energy systems: A bibliographical survey. Renew Sustain Energy Rev 2016;62:32–45.
[104] Lü X, Lu T, Kibert CJ, Viljanen M. Modeling and forecasting energy consumption for heterogeneous buildings using a physical–statistical approach. Appl Energy 2015;144:261–75.
[105] Ghayekhloo M, Menhaj MB, Ghofrani M. A hybrid short-term load forecasting with a new data preprocessing framework. Electric Power Syst Res 2015;119:138–48.
[106] Al-Falahi MD, Wanik MZC. Modeling and performance analysis of hybrid power system for residential application. In: Power Engineering Conference (AUPEC), 2015 Australasian Universities; 2015. p. 1-6.
[107] Shrivastava V, Misra RB. Development of Bayesian belief network model for electrical load demand. Int J Syst Assur Eng Manage 2010;1:170–7.
[108] Panapakidis IP. Clustering based day-ahead and hour-ahead bus load forecasting models. Int J Electr Power Energy Syst 2016;80:171–8.
[109] Al-Falahi MD, Nimma KS, Jayasinghe S, Enshaei H. Sizing and modeling of a standalone hybrid renewable energy system. In: Power Electronics Conference (SPEC), IEEE Annual Southern; 2016. p. 1–6.
[110] Pillai GG, Putrus GA, Pearsall NM. Generation of synthetic benchmark electrical load profiles using publicly available load and weather data. Int J Electr Power Energy Syst 2014;61:1–10.

[111] Guarino F, Cassarà P, Longo S, Cellura M, Ferro E. Load match optimisation of a residential building case study: A cross-entropy based electricity storage sizing algorithm. Appl Energy 2015;154:380–91.
[112] Bahramara S, Moghaddam MP, Haghifam MR. Optimal planning of hybrid renewable energy systems using HOMER: A review. Renew Sustain Energy Rev 2016;62:609–20.
[113] Sharafi M, Elmekkawy TY. Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach. Renewable Energy 2014;68:67–79.
[114] El Alimi S, Maatallah T, Ben Nasrallah S. Break-even analysis and optimization of a stand-alone hybrid system with battery storage for residential load consumption—A case study. Renew Sustain Energy Rev 2014;37:408–23.
[115] Belmili H, Haddadi M, Bacha S, Almi MF, Bendib B. Sizing stand-alone photovoltaic–wind hybrid system: Techno-economic analysis and optimization. Renew Sustain Energy Rev 2014;30:821–32.
[116] Xu L, Ruan X, Mao C, Zhang B, Luo Y. An improved optimal sizing method for wind-solar-battery hybrid power system. IEEE Trans Sustain Energy 2013;4:774–85.
[117] Ma T, Yang H, Lu L, Peng J. Optimal design of an autonomous solar–wind-pumped storage power supply system. Appl Energy 2015;160:728–36.
[118] Kaabeche A, Ibtiouen R. Techno-economic optimization of hybrid photovoltaic/wind/diesel/battery generation in a stand-alone power system. Sol Energy 2014;103:171–82.
[119] Kaldellis JK, Zafirakis D, Kavadias K. Minimum cost solution of wind–photovoltaic based stand-alone power systems for remote consumers. Energy Policy 2012;42:105–17.
[120] Khatib T, Mohamed A, Sopian K, Mahmoud M. Optimal sizing of hybrid pv/wind systems for Malaysia using loss of load probability. Energy Sour, Part A: Recovery, Utiliz, Environ Effects 2015;37:687–95.
[121] Mokheimer EMA, Sahin AZ, Al-Sharafi A, Ali AI. Modeling and optimization of hybrid wind–solar-powered reverse osmosis water desalination system in Saudi Arabia. Energy Convers Manage 2013;75:86–97.
[122] Huneke F, Henkel J, González JAB, Erdmann G. Optimisation of hybrid off-grid energy systems by linear programming. Energy Sustain Soc 2012.
[123] Ferrer-Martí L, Domenech B, García-Villoria A, Pastor R. A MILP model to design hybrid wind–photovoltaic isolated rural electrification projects in developing countries. Eur J Oper Res 2013;226:293–300.
[124] Tan W-S, Hassan MY, Majid MS, Abdul Rahman H. Optimal distributed renewable generation planning: A review of different approaches. Renew Sustain Energy Rev 2013;18:626–45.
[125] Lee SC. Numerical estimation model of energy conversion for small hybrid solar–wind system. Sol Energy 2012;86:3125–36.
[126] Kanase-Patil AB, Saini RP, Sharma MP. Sizing of integrated renewable energy system based on load profiles and reliability index for the state of Uttarakhand in India. Renewable Energy 2011;36:2809–21.
[127] Elliston B, MacGill I, Diesendorf M. Least cost 100% renewable electricity scenarios in the Australian National Electricity Market. Energy Policy 2013;59:270–82.
[128] Gan LK, Shek JKH, Mueller MA. Optimised operation of an off-grid hybrid wind-diesel-battery system using genetic algorithm. Energy Convers Manage 2016;126:446–62.
[129] Merei G, Berger C, Sauer DU. Optimization of an off-grid hybrid PV–Wind–Diesel system with different battery technologies using genetic algorithm. Sol Energy 2013;97:460–73.
[130] Sheng W, Liu K-Y, Meng X, Ye X, Liu Y. Research and practice on typical modes and optimal allocation method for PV-Wind-ES in Microgrid. Electr Power Syst Res 2015;120:242–55.
[131] Abbes D, Martinez A, Champenois G. Life cycle cost, embodied energy and loss of power supply probability for the optimal design of hybrid power systems. Math Comput Simul 2014;98:46–62.
[132] Paliwal P, Patidar NP, Nema RK. Determination of reliability constrained optimal resource mix for an autonomous hybrid power system using Particle Swarm Optimization. Renewable Energy 2014;63:194–204.
[133] Borhanazad H, Mekhilef S, Gounder Ganapathy V, Modiri-Delshad M, Mirtaheri A. Optimization of micro-grid system using MOPSO. Renewable Energy 2014;71:295–306.
[134] Safari S, Ardehali MM, Sirizi MJ. Particle swarm optimization based fuzzy logic controller for autonomous green power energy system with hydrogen storage. Energy Convers Manage 2013;65:41–9.
[135] Fetanat A, Khorasaninejad E. Size optimization for hybrid photovoltaic–wind energy system using ant colony optimization for continuous domains based integer programming. Appl Soft Comput 2015;31:196–209.
[136] Wang R, Purshouse RC, Fleming PJ. Preference-inspired coevolutionary algorithms for many-objective optimization. IEEE Trans Evol Comput 2013;17:474–94.
[137] Kumar R, Gupta RA, Bansal AK. Economic analysis and power management of a stand-alone wind/photovoltaic hybrid energy system using biogeography based optimization algorithm. Swarm Evolution Comput 2013;8:33–43.
[138] Maleki A, Askarzadeh A. Optimal sizing of a PV/wind/diesel system with battery storage for electrification to an off-grid remote region: A case study of Rafsanjan, Iran. Sustain Energy Technol Assess 2014;7:147–53.
[139] Chang K-H, Lin G. Optimal design of hybrid renewable energy systems using simulation optimization. Simul Model Pract Theory 2015;52:40–51.
[140] Mukhtaruddin RNSR, Rahman HA, Hassan MY, Jamian JJ. Optimal hybrid renewable energy design in autonomous system using Iterative-Pareto-Fuzzy technique. Int J Electr Power Energy Syst 2015;64:242–9.
[141] Abdelhak BJ, Najib E, Abdelaziz H, Hnaien F, Yalaoui F. Optimum sizing of hybrid PV/Wind/Battery Using Fuzzy-Adaptive Genetic Algorithm in real and average battery service life. In: International symposium on power electronics, electrical drives, automation and motion; 2014. p. 871–76.
[142] Lujano-Rojas JM, Dufo-López R, Bernal-Agustín JL. Probabilistic modelling and analysis of stand-alone hybrid power systems. Energy 2013;63:19–27.
[143] Hong Y-Y, Lian R-C. Optimal sizing of hybridwind/PV/diesel generation in a stand-alone power system using markov-based genetic algorithm. IEEE Trans Power Delivery 2012;27:640–7.
[144] Askarzadeh A. A discrete chaotic harmony search-based simulated annealing algorithm for optimum design of PV/wind hybrid system. Sol Energy 2013;97:93–101.
[145] Maleki A, Khajeh MG, Rosen MA. Weather forecasting for optimization of a hybrid solar-wind–powered reverse osmosis water desalination system using a novel optimizer approach. Energy 2016;114:1120–34.
[146] Khatib T, Mohamed A, Sopian K. Optimization of a PV/wind micro-grid for rural housing electrification using a hybrid iterative/genetic algorithm: Case study of Kuala Terengganu, Malaysia. Energy Build 2012;47:321–31.
[147] Tahani M, Babayan N, Pouyaei A. Optimization of PV/Wind/Battery stand-alone system, using hybrid FPA/SA algorithm and CFD simulation, case study: Tehran. Energy Convers Manage 2015;106:644–59.
[148] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Appl Energy 2010;87:1059–82.
[149] (1 Oct). Webinar minigrid homer energy. Available: <https://cleanenergysolutions.org/sites/default/files/documents/webinar-minigrid-homer-energy.pdf>.
[150] (2016, 1 Oct). Homer Energy. Available: <http://www.homerenergy.com/HOMER_pro_modules.html>.
[151] P. Lilienthal. (1 Oct). Homer Energy. Available: <https://d2oc0ihd6a5bt.cloudfront.net/wp-content/uploads/sites/837/2016/03/Peter-Lilienthal-HOMER-Pro-Software.pdf>.
[152] Khalid F, Aydin M, Dincer I, Rosen MA. Comparative assessment of two integrated hydrogen energy systems using electrolyzers and fuel cells. Int J Hydrogen Energy 2016;41:19836–46.
[153] Baghdadi F, Mohammedi K, Diaf S, Behar O. Feasibility study and energy conversion analysis of stand-alone hybrid renewable energy system. Energy Convers Manage 2015;105:471–9.
[154] Olatomiwa L, Mekhilef S, Ohunakin OS. Hybrid renewable power supply for rural health clinics (RHC) in six geo-political zones of Nigeria. Sustain Energy Technol Assess 2016;13:1–12.
[155] Maatallah T, Ghodhbane N, Ben Nasrallah S. Assessment viability for hybrid energy system (PV/wind/diesel) with storage in the northernmost city in Africa, Bizerte, Tunisia. Renew Sustain Energy Rev 2016;59:1639–52.
[156] Hossain M, Mekhilef S, Olatomiwa L. Performance evaluation of a stand-alone PV-wind-diesel-battery hybrid system feasible for a large resort center in South China Sea, Malaysia. Sustain Cities Soc 2017;28:358–66.
[157] Bentouba S, Bourouis M. Feasibility study of a wind–photovoltaic hybrid power generation system for a remote area in the extreme south of Algeria. Appl Therm Eng 2016;99:713–9.
[158] (2017, 3 March). Hybrid Optimization by Genetic Algorithms software. Available: <http://personal.unizar.es/rdufo/>.
[159] Dufo-López R, Bernal-Agustín JL. A comparative assessment of net metering and net billing policies. Study cases for Spain. Energy 2015;84:684–94.
[160] Dufo-López R, Lujano-Rojas JM, Bernal-Agustín JL. Comparison of different lead–acid battery lifetime prediction models for use in simulation of stand-alone photovoltaic systems. Appl Energy 2014;115:242–53.
[161] Schiffer J, Sauer DU, Bindner H, Cronin T, Lundsager P, Kaiser R. Model prediction for ranking lead-acid batteries according to expected lifetime in renewable energy systems and autonomous power-supply systems. J Power Sources 2007;168:66–78.
[162] Dufo-López R, Bernal-Agustín JL, Yusta-Loyo JM, Domínguez-Navarro JA, Ramírez-Rosado IJ, Lujano J, et al. Multi-objective optimization minimizing cost and life cycle emissions of stand-alone PV–wind–diesel systems with batteries storage. Appl Energy 2011;88:4033–41.
[163] Muhsen DH, Ghazali AB, Khatib T. Multiobjective differential evolution algorithm-based sizing of a standalone photovoltaic water pumping system. Energy Convers Manage 2016;118:32–43.
[164] Abbes D, Martinez A, Champenois G. Eco-design optimisation of an autonomous hybrid wind–photovoltaic system with battery storage. IET Renew Power Gener 2012;6:358–71.
[165] Vergara PP, Rey JM, Silva LCPd, Ordóñez G. Comparative analysis of design criteria for hybrid PV/wind/battery systems. IET Renew Power Gener 2016.
[166] Perera ATD, Attalage RA, Perera KKCK, Dassanayake VPC. A hybrid tool to combine multi-objective optimization and multi-criterion decision making in designing standalone hybrid energy systems. Appl Energy 2013;107:412–25.
[167] Dufo-López R, Cristóbal-Monreal IR, Yusta JM. Stochastic-heuristic methodology for the optimisation of components and control variables of PV-wind-diesel-battery stand-alone systems. Renewable Energy 2016;99:919–35.
[168] Maheri A. Multi-objective design optimisation of standalone hybrid wind-PV-diesel systems under uncertainties. Renewable Energy 2014;66:650–61.
[169] Perera ATD, Attalage RA, Perera KKCK, Dassanayake VPC. Designing standalone hybrid energy systems minimizing initial investment, life cycle cost and pollutant emission. Energy 2013;54:220–30.