An overview of optimization techniques used for sizing of hybrid renewable energy systems

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Variability of renewables like solar and wind remains a major concern, despite a substantial decrease in the capital cost of their power conversion devices. One of the methods to improve the reliability of power is to combine more than one renewable power sources and storage systems together, as per the local renewable potential, is called a hybrid renewable energy system (HRES). The exact sizing of individual sources and storage systems to fulfill the respective load demand for the renewable potential of the site is not a straightforward task. Different sizing and optimization methodologies are developed by the research community. A comprehensive overview of the literature of these methodologies is carried out in this paper. Classical techniques were being applied to the HRES sizing, but their limitations led researchers to increasingly look for multi-objective heuristic techniques. This has led to a range of evolutionary algorithms being employed lately. The robustness of these techniques made them an effective tool for the search of global optimum, but their convergence speed may well be slower in comparison to gradient-based methods in the vicinity of the optimum point. It is needed to come up with novel hybrid techniques, which can carefully combine the conventional and evolutionary techniques by augmenting their advantages and at the same time avoiding their shortcomings. The literature survey proves that HRES from very small capacity of a few watts to many megawatts have been proposed for a variety of different locations throughout the world with varying degrees of cost of energy.

Introduction

Environmental degradation is anthropogenic [1] in its origin, is well established scientific fact. The urgency [2] of mitigation of the problem, before it reaches the point of no return, has put an enormous responsibility on researchers and policymakers [3]. Many sections of the population in developing countries [4] are yet to realize the fruits of full access to electricity. In addition to this, the much-anticipated shift of the transport industry from petroleum-based fuels to electrification will increase the electric power demand in developed countries [5] as well. Renewable energy sources have the potential to be the solution out of this conundrum. Widespread adaption of renewable energy has not been achieved, one of the reasons being its unfavorable economics. The initial cost of renewable energy extraction devices used to be very high in comparison to conventional alternatives. Although the source of energy is free and abundant in nature. Technological advances in manufacturing coupled with mass production [6] have solved the issue of installation cost largely. Another issue with renewable energy is that it has to be utilized spontaneously, as we have no control over the occurrence of the natural phenomenon [7] from which the solar plant and Wind turbines get input energy. The very nature of the resources is prone to fluctuation in the availability on the mercy of nature.

One solution to iron out the fluctuation in output of renewable sources, workable in most cases, can be to club more than one renewable energy together. The combination can be of a renewable source either with a conventional source or with one or more other renewable sources [8] as shown in Figure 1. This integration

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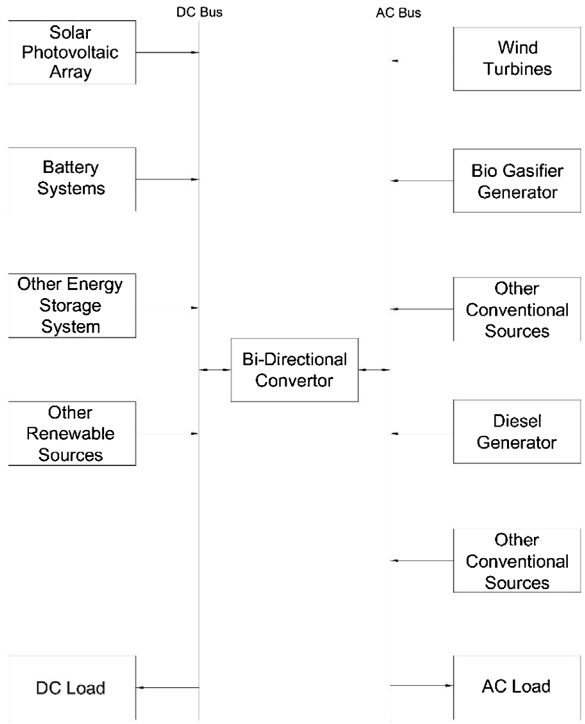

FIGURE 1
Schematic of typical HRES (choice of sources and storage systems may vary as per the on-site renewable potential and designer's preferences).

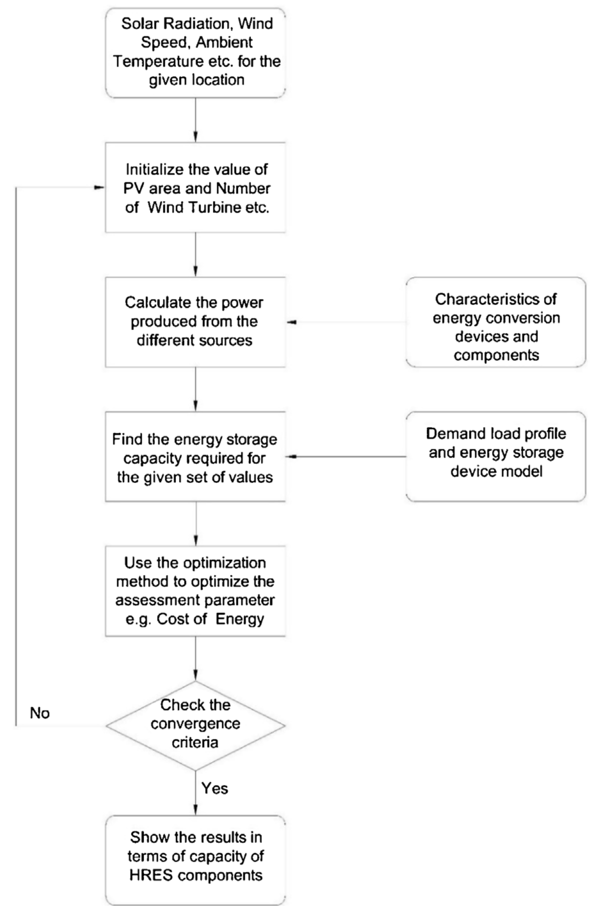

FIGURE 2
Flow chart of the typical optimization of PV-WT HRES.

has the potential to scale down the storage capacity significantly. This is called Hybrid Renewable Energy Systems (HRES). HRES can be a combination of one renewable energy source with other renewable or conventional sources. It may or may not have an energy storage device of any kind coupled with it. When HRES is grid-connected, the grid can be modeled as a battery of infinite size. A variety of combinations of solar photovoltaic, solar thermal, wind turbine, biogas, producer gas, geothermal energy, hydrogen fuel cell (it can replace the battery), diesel generator, batteries etc. have been tried for modeling and optimization of HRES. Hybrid renewable energy plant can serve as an energy supplier to heating, cooling or multi-generation purposes as well [9]. Many researchers are considering the HRES as a viable source of energy to fulfill the potable water requirements of communities and industries [10].

The stochastic nature of the natural resources, a non-linear variation of output power from PV array and Wind Turbine, the choice of the type of components and their orientation and economic model of Cost of energy generated by HRES [11]; makes the optimization problem of HRES very complex as shown in the Figure 2. This fact has led the researchers to develop many methods and techniques for optimization of HRES. Zhou et al. [12] have done an extensive review of grid-independent hybrid solar and wind systems. Modeling of components is considered crucial as it will affect the final outcome of problem greatly. For example, a small difference in temperature coefficient of solar PV cell will affect the annual outcome significantly. Three artificial intelligence techniques are reviewed as well. The need of multi-objective work for HRES and lack of economic viability of FC based HRES [13] is highlighted by Bernal-Agustín et al. Nema et al. [14] reviewed the developments in HRES field and showed that apart from modeling, proper energy control and management is an important part of system development. In the review of stand-alone HRES focused on PV, Bajpai and Dash [15] presented various types of models of components including solar (electrical models and thermal models), fuel cells, electrolyzer, hydrogen tank, ultra-capacitor, battery, diesel generator and power conditioning equipment (MPPT techniques) are elaborated.

Brief of sizing techniques along with assessment parameters is given by Luna-Rubio et al. [16]. Erdinc and Uzunoglu [17] summarized the research on HRES optimization using artificial techniques and also proposed the new promising techniques. Storage options for micro grid are briefed including types of batteries, which tend to be bottleneck in the implementation of clean energy options. Multi-objective optimization techniques applied to HRES are reviewed by Fadaee and Radzi [18]. They concluded that there is need of research on application of multi-objective optimization methods in HRES. Optimal placement is detailed by the Tan et al. [19] at length with description of conventional techniques, modern techniques and potential future techniques. They concluded that the problem of placing of Distributed Renewable Generation (DRG) needs systematic treatment in order to increase the attraction towards it.

Deshmukh and Deshmukh [20] reviewed the modeling of renewable sources and hybrid systems comprehensively. This gives an idea about the breadth of the field and its multidisciplinary nature. They suggested more work in HRES with sources other than PV-WT and for grid-connected systems. Trends in the optimization of solar PV-wind based HRES are outlined with detailed input data requirement modeling of main components by Sinha and Chandel [21]. A brief overview of optimization of HRES optimization by covering various techniques of HRES sizing is done by Bhandari et al. [22].

Energy management system for the HRES is a crucial aspect of the operations. Linear programming and including artificial intelligence techniques [23] are used for this purpose. The publications on the optimal location of renewable sources for distributed generations is reviewed by Admouleh et al. [24] with a fine description of modern optimization techniques. The policy of regional and federal governments affects the affordability of HRES [25]. The incentives and subsidies for the installation of REs can go a long way in the accelerated adaption of HRES. The potential of PV-WT based HRES system for Oman was studied by Al Busaidi et al. [26] and two case studies are compared. A very structured review of PV-WT HRES by Al Falahi et al. [27] and the importance of multi-objective optimization is emphasized. Eriksson and Gray [28] highlighted the lack of use of Fuel Cell technology for HRES and the need for a dedicated software tool for modeling of FC-HRES system. The evolution of policy apparatus for renewables in India and way forward for the hybrid plants is surveyed by Das et al. [29]. Addition of Bio with PV and WT can go a long way for higher renewable penetration in countries like India as highlighted by Bisht and Thakur [30]. Looking into all these review papers, need for a comprehensive review of the literature was felt. The motivation, objectives and salient features of this manuscript are described in the following subsection.

Motivation and objectives

The increasing share of variable energies in the energy mix has amplified the concern of energy policymakers regarding the temporal mismatch between load demand and renewable energy supplies. HRES are poised to play an important role to come out of this conundrum. Looking into the importance of the proper sizing HRES at the pre-installation stage, the search for optimal configuration of HRES is imperative. The literature on this field is quite extensive in terms of techniques used and the time period over which it is used. As is evident from the attempts to review the field of optimal configuration of HRES, they are generally focused on a specific aspect of HRES design. Looking into the aforementioned literature, their scope and the breadth of the literature surveyed, the need for a fresh review of a broad range of HRES sizing optimization literature was felt. In addition to that new research papers published on the subject create space for an effort to revisit the literature on the subject. This paper is the culmination of the efforts done in that direction.

The recent advances in modern techniques and their applications in the field of HRES optimization resulted in the need for the review of the subject, which includes cutting edge studies done in the field and critically examining the way forward. In this study, the classification of HRES optimization studies is done based on the optimization techniques used and information is tabulated for better representation. The type of energy sources and energy storage devices used are also presented in addition to the configuration of the system connectivity. It further identifies the combination of energy resource and energy storage technologies and their topographies in terms of connectivity with the larger grid. This manuscript is also aimed to reveal the set of combinations and their final selection of the preferable energy mix for the given geographies. It is expected that this manuscript will add value to the literature on the optimal configuration of HRES.

The salient features of this study are its inclusion of a wide range of renewable energy sources and energy storage methods. It also identifies the category of assessment parameters of the concerned studies. The objectives beyond economics and reliability are also considered. Further, it builds the flow in a chronological way for a given set of optimization techniques, which gives an idea about the evolution of the optimization methods used in HRES sizing. The architecture of power connection is also pointed out to understand the nature of HRES configuration. The location of the case study gives an idea about the type of HRES studies done in the different geographic and economic contexts. The inclusion of the size of the system as the feature of the study of literature highlights the range of scale considered for the HRES. The final result of the cost parameter of the optimal system gives an outlook in terms of the economic favorability of HRES systems going forward.

The remaining paper is organized as follows: Section ''Conventional techniques applied to HRES optimization'' deals with the use of conventional techniques for HRES optimization. Section ''Modern optimization techniques for HRES sizing'' delves into the modern techniques utilized for the optimal configuration of HRES. Section ''conclusions and discussion'' concludes the material for a comprehensive understanding of the topic.

Conventional techniques applied to HRES optimization

Classical techniques of optimization are deterministic in their methodology. They try to find the global optimum of the set of the equations using mathematical formulations like linear programming (LP), Nonlinear programming (NLP), Iterative techniques, Graphical techniques, Quadratic Programming (QP), Dynamic Programming (DP) etc. The advantage of these methods is that they provide definite answer [31] but the demerit is that they cannot handle a large number of variables in complex space.

Graphical technique

If the sizing variables are two, the graphical technique can be used for the fairly intuitive representation of the sizing problem [32]. Graphical techniques give first hand observation of the impact of the change of the size of components on assessment parameters of the HRES system. Borowy and Salameh [33] have done modeling and optimization of PV-wind system with battery for the given number of Wind Turbines for the typical house of Massachusetts, USA. They used LPSP as reliability criteria and system cost as economic criteria with programming in PASCAL. This is one of the initial attempts to optimize the sizing of HRES system to minimize the cost of the system. Five sites of Corsica Island, France were considered by Diaf et al. [34] for the optimal configuration of Hybrid Photovoltaic and Wind System. It is noted that sites with lower wind potential have a higher cost of energy. Celik [35] has developed the methodology for sizing of PV & WT, which finds the monthly average of resources and adds the standard deviations to it. It is claimed that for the site under consideration, this method is the most appropriate. This method doesn't require the hourly values of renewable energy resource availability and thus makes macro analysis only. Saheb-Koussa et al. [36] used a deterministic approach to optimize the size of HRES for four different sites of Algeria with detailed modeling of components in MATLAB/Simulink with TIC (Total Investment Cost) as criteria taking monthly averages of solar and wind data.

In most cases, this method can optimize only two parameters of the system e.g. size of PV and size of WT. The other parameters e.g. size of the battery, LPSP etc. are decided by the designer using the experience and physics of the problem. The other parameters, which are not computed as decision variables in the calculation, e.g. LPSP, size of the battery etc. can also be found with iterative procedures by changing their values in the logical range with entire new calculations. Inherent capabilities of this technique have led it to be used for HRES sizing for a long time as evident from Table 1. This method is used for the optimization of HRES system in developing and developed parts of the world some-time back. It is used for the remote areas of Canada, Algeria and for combined heat system in the UK, US and Germany. The purpose of the HRES in many of these cases is to augment existing conventional sources of energy in many of these cases. This has led designers to explore the parameters other than the cost of electricity as is evident from Table 1. This technique is simple to implement and easy to understand. It was used early on by researchers for the optimal configuration of HRES. The involvement of the designer's discretion in deciding certain parameters, while using this method, gave the way to other methods gradually. The optimization techniques, which can handle the larger number of decision variables have gained more popularity nowadays.

Iterative techniques

One of the simple ways to search for the optimal variable values is to search for them iteratively by calculating possible combinations of variables and finding corresponding objective function values. The value of the objective function of successive iteration is compared with the values of the objective function of earlier operations. The set of design variable values resulting in the preferable objective function are retained. The other combinations of variables are discarded progressively in iterative operations. The procedures of the iterative search are fine-tuned in many ways, giving rise to a wide range of numerical techniques. The iterative techniques have been employed by a number of researchers, the brief of which is in the following paragraphs.

Isherwood et al. [39] proposed the wind-diesel system for Alaskan village among several studied systems including WT-FC. The solver used is Super Code, the in-house code of National Lawrence Laboratory. Hocaoğlu et al. [40] proposed a novel optimization methodology for Wind-PV-Battery system using alternative and deterministic approach. They initially found the maximum capacity of the battery by calculation using the total load and solar–wind potential. Then, the enumerative method is applied to find the deterministic value of the optimal configuration. Hybrid PV/wind system for a household residence in Algeria has been optimized by Kaabeche et al. [41] using DPSP (Deficiency of power supply probability) and LUEC (Levelized Unit Energy Cost) as assessment parameters with development of MATLAB program. Kaabeche et al. [42] developed the algorithm for optimal sizing of PV-WT HRES with the iterative method using MATLAB. They used several criteria like DPSP, REPG, TNPC and BEDA for a case study at the CDER, Algeria. Iterative technique is performed by Hossam-Eldin et al. [43] for PV, WT, BS and DG based HRES for power along with desalination process. The PV-micro turbine system is designed [44] for the rural community of Palestine including the PV degradation with time.

Kaabeche and Ibtiouen [45] optimized the PV-WT-DG-Battery system for a site in the Algeria reliability of zero total energy deficit using MATLAB using the iterative technique for given capacity of Battery and changing the values of the number of PV panels and wind turbines in a range. It is shown that this system is more economical compared to the system without DG. Iterative technique is implemented in MATLAB by Smaoui et al. [46] to optimize the PV, WT and Hydrogen system with desalination for 14,400 inhabitants. Eltamaly et al. [47] used hybrid-2 architecture and iterative method in MATLAB to optimize the HRES as per the load classification of high priority load and low priority load. The iterative technique is employed by Mohamed et al. [48] in MATLAB for a site in Saudi Arabia. The results are compared with HOMER & GA. The iterative technique is employed by Kougias et al. [49] for PV-small hydro HRES with coding for enumerative search methodology in the MATLAB. They concluded that calculated change in azimuth and tilt angle PV panels increases corresponding matching with hydro resources in terms of meeting the demand properly, despite compromising a bit on the total energy production from the solar resource. Hosseinalizadeh et al. [50] studied the four sites in Iran using the developed model and concluded that FC does not turn up in the optimal system, because of the high initial cost. RO-MSF based desalination system is developed for the region of Tehran, Iran by Heidary et al. [51] using MATLAB environment.

Table 2 presents the publications using iterative techniques for HRES optimization. For the system with numerous renewable energy sources and energy storage facilities, the calculation of a large number of combinations of decisions will require computational time accordingly. It was seen that, for fairly complex systems, these may take more computation time compared to other methods. This method optimizes one objective only e.g. cost function of the system. Therefore, other decision parameters like the reliability of the system can be found by the simulation modeling for the given sizes of HRES components as an additional parameter. Literature survey shows that this technique is used for the locations of mainly developing countries like India, China and countries of North Africa. The size of systems is also not that large, which means it is used in the case studies of smaller power requirements. The cost of energy in these studies ranges from 0.1 to 3.5 $/kWh.

Linear programming

The linear programming has evolved since its development in the first half of the 20th century and is being widely used in the field of industrial engineering for assignment and root problems. It can handle linear functions in business models effectively. Many researchers tried to employ the linear programming method to the HRES sizing problem. By doing so, one can use well-developed and robust linear programming techniques in HRES [56] design

TABLE 1

Graphical techniques used for the HRES optimization.

PV	WT	BS	CAES	DG	Tool used	Economic criteria	Reliability criteria	GC/SA	Architecture	Location	Power demand load	Cost	Highlights	Ref.
√	√	√		√		PT		SA		Oldenburg, Germany	10,000 kW h per year	10.4 years payback time	A building of the university, not connected to the grid, consuming 1000 kW h approximately per year was considered for HRES. Renewable fraction and payback time are considered for optimization.	[37]
√	√	√			PASCAL	System Cost	LPSP	SA	DC	Massachusetts was, USA	0.14–1.4 kW	–	30 year recorded met data is used to size the HRES system for the typical house in Massachusetts. The MPPT based model is implemented in PASCAL and graphs of size of PVs v/s size of BS are plotted for given LPSP.	[33]
√	√	√			SEU-ARES	SC		SA		Cardiff, UK	15 W	1–3.6 $/kW h	Average size of PV and WT are calculated for every month of the year. Then the average of the year is calculated and the standard deviation is added to it. This is proposed as the size of the equipment, as an increase in the size beyond this will not yield much on the reliability against an increase in the cost.	[35]
√	√	√		√	MATLAB SIMULINK	TC		SA	DC	Algeria	3.5–4.1 kW	10.8 $/kW h	Three sites in Algeria are simulated in MATLAB/SIMULINK for the sizing of HRES. The site with higher potential of the wind came out with more wind turbine numbers in comparison to other two sites.	[36]
√	√	√				LCE	LPSP	SA	DC	Corsica Island	100–700 W	2.1–3.4 $/kW h	Five sites of Corsica Island, France are studied for PV-WT based HRES, with similar solar potential and varying wind potential. It was observed the COE of the HRES was better than the conventional system, especially in the regions of high wind potential.	[34]
	√		√	√		COE		SA	AC	Quebec, Canada	–	–	WT in conjunction with DG supported by CAES proves to be saving of 50% for the remote locations of Canada, where DG is a dominant source of energy.	[38]

TABLE 2

Iterative techniques used for the HRES optimization.

PV	WT	MH	other source	BS	FC	DG	Tool used	Economic criteria	Reliability criteria	GC/SA	Architecture	Location	Power demand load	Cost	Highlights	Ref.
√	√			√				LCE	LPSP	SA		Guangdong, China	1000 W	0.4–0.5 $/kW h	Telecommunication base station with constant load need, at an island in China, is sought to be powered by HRES. 2 days of autonomy system give economically better results.	[52]
	√	√						LCC		SA		Kerala, India	20–27 kW	0.1 $/kW h	Iterative technique is employed to size micro-hydro, wind and BS based HRES for a remote village in India with 120 families. The results show that reliable and economic power supply can be provided by HRES.	[53]
√	√			√				LCE	LPSP	SA	DC	Corsica Island	80–320 W	0.8–1.7 $/kW h	Three sites of Corsica Island are studied for HRES. It was observed that COE strongly depends on the renewable potential of the site. In addition to that, COE increases sharply for very low LPSP with increased reliability.	[54]
√				√	√			COST		SA	DC	Shanghai, China	1.4–2.3 kW	0.9–1.2 $/kW h	Fuel cell and BS are coupled with PV for long term and short term energy storage in HRES.	[55]
√	√			√			MATLAB	LUEC	DPSP	SA	DC	Algeria	80–340 W	1–3.5 $/kW h	PV, WT and BS based HRES is implemented for the household in Algeria, using local solar and wind data, for grid autonomous scenario.	[41]
√	√			√		√		COE, COW				Egypt	55–70 kW	0.06–0.08 $/kW h	Reverse osmosis along with power production using HRES is studied for the site in Egypt. It was observed that a further decrease in PV price can bring the HRES to the grid parity.	[43]
√	√				√		MATLAB	COST		SA	DC	Kerkennah islands, Tunisia	1050 kW	Desalination unit	HRES, for desalination plant, for Tunisian island is sized to satisfy the fresh water requirement of 14,400 inhabitants and tourists coming in.	[46]
√	√			√		√	MATLAB	LEC	LOLP	SA	H2	Saudi Arabia	5–27 MW	0.35–0.38 $/kW h	The load is prioritized as per importance and bifurcated for the preferential supply in this study. Five sites in Saudi Arabia are studied for HRES using MATLAB coding.	[47]

and sizing, although with initial assumptions in the modeling to make it a linear model. In addition to that, the availability of commercial software to solve the linear programming problems makes it easy to deploy this technique for HRES configuration.

Chedid and Rehman [57] proposed a deterministic approach using linear programming technique with EENS (Expected energy not supplied) as reliability criteria for a location of Lebanon with 800 kW load. Both the cases of the Grid-connected and Standalone system are considered. Linear programming is employed by Zhan et al. [58] to optimize PV-DG-BS system via power dispatch simulation with coding in MATLAB. Mixed-Integer Linear Programming is utilized by Dai and Mesbahi [59], where CPLEX solver is employed for programming solution to minimize the cost of energy. Mixed-integer linear programming [60] based on superstructure model is proposed for WT, PS and DG based HRES system at K-island, Taiwan. Algebraic power pinch analysis [61] with Mixed-integer linear programming is utilized for grid-connected HRES system for hourly calculations of energy balance.

Linear programming in GAMS software is employed by Huneke et al. [62] to optimize the HRES design and actual testing of two sites, one in India and the other in Colombia, with PV, WT, BS and DG combination. A sparse matrix is used with linear programming to optimize the energy cost for AC bus based HRES system for the location in Korea [63]. Grid-connected Combined Heat and Power (CHP) system is optimized using LP2 model in EnergyPro Software by Wang et al. [64], where day ahead weather data schedule is used. Linear programming with superstructure [65] based methodology is applied to PV, WT and BS based Stand-alone HRES. Optimization of HRES system with PV-BIO-DG for a rural area of Bihar, India is done using mixed-integer linear programming with a rolling horizon scheme [66] to minimize the levelized cost of energy. The data time series in this study has a time frame as low as 10 min.

Table 3 summarizes the use of linear programming in HRES optimization. Various forms of linear programming and solvers are utilized for the HRES sizing. The need for large data handled for HRES sizing necessitates the use of equation solvers (e.g. GAMS, CPLEX) or in-house coding for the solution. In addition to that, one needs to identify the values of the coefficient of variables in the linear equation. The conversion of an essentially non-linear model of renewable power production to a linear one, as seen in the reviewed papers, makes it susceptible to inaccuracies in calculations. That's why one should be careful in using linear programming methods for HRES optimal configurations. The HRES systems with the load ranging from a few kW to several MW scale are optimized using linear programming in all types of geographies, as it can be deployed using commercially available software. The cost of energy forecasted in these studies is also in the reasonable range of 0.1–0.3 $/kWh.

Other classical techniques

The problem of sizing of HRES is non-linear inherently because of the non-linear behavior of component characteristics and complex objective function. For example, the variation of output power from wind turbines is not a linear function of wind speed. This results in non-linear programming [67] of the optimization problem for HRES. A variety of non-linear programming methods have been attempted by the researchers for that aim. The various ways to solve this problem have been attempted as shown in the following paragraphs.

Zervas et al. [68] developed the methodology to optimize PV-FC system and implemented it for the household in Greece using the fundamental rolling horizon principle of Model Predictive Control (MPC). This method predicts Global Solar Irradiance (GSI) using the radial bias function of neural network architecture. Grid-connected PV, WT and storage based HRES system is optimized using Non-linear programming in GAMS software by Berrada and Loudiyi [69]. Jursaz and Ciapaa [70] studied a similar grid-connected system with a run of the river plant using MINLP in MS-EXCEL based GRG tool. Belfkira et al. [71] used the DIRECT (DIviding RECTangles) algorithm to optimize the HRES with 15 kW pick capacity for the site of Senegal using measured data of solar radiation, wind speed and ambient temperature for over a year. The energy hub model is used by Real et al. [72] with Mixed-integer quadratic programming in MATLAB to optimize the wind – FC – Battery system.

Tazvinga et al. [73] minimized the cost of PV-DG-Battery system for a rural community in Zimbabwe considering different load for weekdays and weekends as well as for summer and winter using MATLAB. Dagdoughi et al. [74] developed the dynamic decision model to optimize the system for green building heating pumping and power requirements using PV, WT, BIO, FPC and Battery for the municipality in Italy. The multi-objective objective function is used in this model and is solved using Lingo 10 for the stochastic demand and supply conditions. Alsayed et al. [75] presented several multi-criteria optimization methods for HRES with different weighing methodologies. Multi criteria analysis used are (1) Weighted Sum Method (WSM), (2) TOPSIS (Technique for order preference by similarity with ideal system) and (3) Preference ranking organization method for enrichment evaluation (PROMETHEE II).

Guinot et al. [76] employed SPEA-2 in ODYSSEY tool to optimize the HRES system with a hybrid architecture, where the effect of aging in the performance of components is also considered. Erdinc and Uzunoglu [77] presented the observe and focus algorithm to minimize the unit cost of energy for the PV-WT-FC-BS system using MATLAB-Simulink with consideration for component degradation. Yang and Nehorai [78] provided the framework of joint optimization to configure the multi-storage HRES with DG as a consensus problem with a calculated example.

Abdullah et al. [79] presented the tradeoff analysis for multi-objective optimization of HRES system in MATLAB. Distributed Energy Resources Customer Adoption Model (DER-CAM) is employed to optimize the grid-connected PV-BS based system for the research institute building area by Ref. [80]. The Island in Central Greece [81] is considered for the PV-WT-PS HRES system whereby surplus energy is used to produce the hydrogen through electrolyzer, where THESIS and PYTHON tools are employed. Kasseris et al. [82] presented the economic feasibility of the WT-FC system for Greek Island. Stochastic multi-integer programming based on benders decomposition algorithm is utilized for WT and BS HRES system and it is compared with the results of Gurobi solver.

The HRES system with desalination is programmed for a village on the Greek island for seasonal population variation [83] and subsequent Power and freshwater requirement of the community.

TABLE 3

Linear programming used for the HRES sizing.

PV	WT	BIO	MH	BS	PS	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	GC/SA	Architecture	Technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√			√			√		COE	EENS		SA/GC		LP-Det	Lebanon	550–800 kW	0.1–0.16 $/kW h	Linear programming based model for HRES optimization is proposed. A case study for the site in Lebanon is presented. The environmental credit for green power is included in the calculations.	[57]
√	√			√			√	GAMS	COE			SA	AC	LP	India	69–114 kW	0.3 $/kW h	Two sites, one in India and the other in Colombia, are studied for HRES installation with proposed method implemented through General Algebraic Model Software.	[62]
√				√			√	CPLEX Solver	COE			SA		MILP	USA	1–14 kW	0.13 $/kW h	A general model for HRES using mixed-integer linear programming is proposed, which integrates the management on both sides of demand and supply.	[59]
√	√					√		GAMS	TC			SA		LP	Taiwan	10–60 kW	–	Superstructure based linear program is presented and solved in GAMS environment for three different scenarios by minimizing the outsourced energy and storage capacity.	[65]
√	√		√			TES		EnergyPro	COST			GC		LP	Finland	12–22 MW	–	Linear model for district heating and power requirement is developed for the estimation of the power availability and reliability. The day ahead forecast is suggested for accurate demand and supply side management.	[64]
√	√			√			√		TSC		EE	SA	AC	LP	Deokjeok Island, Korea	200–1000 kW	0.24 $/kW h	Hourly simulation of HRES supply is executed for the Korean island using a linear programming technique. The load is calculated using EnergyPro software. The results are compared with the results of HOMER.	[63]
√		√					√	Gurobi	LCOE			SA	AC	MILP	India	25–120 kW	0.18–0.23 $//kW h	HRES system based on ORC by solar and DG by bio gasifier is studied for the rural region of India.	[66]
√	√			√					COE NPV			GC		MILP	Malaysia	60 kW	0.1 $/kW h	Mixed-integer linear program is presented and applied for the residential area and industrial area. Lead-acid batteries are favoured over super capacitors, owing to their economics.	[61]

TABLE 4

Other classical techniques for sizing of HRES.

PV	WT	BIO	MH	FPC	BS	FC	PS	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	Social criteria	GC/SA	Architecture	Technique used	Location	Power demand load	Cost	Highlights	Ref.
√						√				GAMS	TC				GC	DC	MINLP	Athens, Greece	0.1–1 kW	0.63–1.64 $/kW h	HRES with hydrogen as energy storage media and solar PV is modeled as non-linear program. The prediction of solar radiation is based on neural network training. Case study for the household in Athens is done.	[68]
	√				√	√				MATLAB	Cost				SA		MIQP	Spain	100–550 W	12–16 k$	Energy hub concept is employed to size WT, BS and FC based HRES along with sensitivity analysis.	[72]
√	√				√				√		TC				SA	DC	DIRECT	Senegal	4–15 kW	388 k€	The case study of the site in Senegal is presented for the sizing PV, WT and BS system using a divided rectangle deterministic method of optimization.	[71]
√	√				√	√				MATLAB SIMULINK	ACS UCEE				SA/GC		O&F	Turkey	18–52 kW	2.2 $/kW h	Observe and Focus algorithm is applied to optimize the HRES, where the effect of decreasing efficiency of the system	[77]
√	√	√		√						LINGO 10	Energy from grid				GC + SA		MPC	Italy	1.3–2.3 kW	–	Dynamic decision model for optimal energy management for HRES with or without storage is developed to satisfy the power, heat and water needs of the building. The cost of energy of the system with storage comes out to be better.	[74]
√	√				√						TC				SA		B&B	USA	1.2–2.8 kW	7178 $	Branch and bound method coupled with generalized reduced gradient method is used to optimize the size of HRES with details of different parameters used.	[88]
√	√				√						TC				SA		PoPA	Malaysia	81 kW	–	Power pinch analysis is extended to include the losses in HRES for optimal sizing of the components of the system as a powerful visualization technique.	[89]
	√				√					Bender's decomposition algorithm	COE				SA		MIP	USA	32–50 MW	–	Constrained stochastic problem is solved using Benders decomposition with Pareto-optimal cuts using a modified Magnanti-Wong method and maximum feasible subsystem generated cuts.	[90]

TABLE 4 (*Continued*)

PV	WT	BIO	MH	FPC	BS	FC	PS	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	Social criteria	GC/SA	Architecture	Technique used	Location	Power demand load	Cost	Highlights	Ref.
√					√				√	MATLAB	Fuel cost				SA		Quadratic	South Africa	1.2–3.8 kW	–	Fuel consumption is minimized considering different load profiles for weekdays and weekends as well as for summer and winter seasons.	[73]
√	√										COST		Emission reduction	Social acceptance	GC		PROMETHEE	Italy	48–200 kW	0.11–0.13 €/kW h	Three types of multi-objective optimization techniques are used to optimize the HRES. WSM, TOPSIS and PROMETHEE-2. The social acceptance model is formulated and is considered as an assessment parameter.	[75]
√	√				√		√		√	CVX TOOLBOX	TC				SA		ADMM	USA	0.6–1.8 MW	5–32 M$	Joint optimization model for the combined optimization of HRES with storage is presented and applied for three sites in the US with different climate patterns.	[78]
√					√	√				ODYSSEY	COE	MDPFT			SA	H1	SPEA 2	Nigeria	15–130 kW	0.8–0.85 €/kW h	Three combinations PV-DG, PV-BS and PV-BS-FC are evaluated. PV-BS-FC comes out to be better than PV-BS, because of high-cost batteries. It is shown that with increase in the cost of diesel, it can also become competitive in comparison to PV-DG.	[76]
√	√				√					MATLAB	LCE	ERED	EEE		GC	H2	ToA	Australia	1.05–1.8 MW	0.13–0.19 $/kW h	Multi-objective optimization includes the life cycle cost for the calculation of embodied emissions of energy and expected renewable energy deficiency as reliability criteria.	[79]
√	√					√	√			THESIS PYTHON	OC				SA		Dynamic	Greece	4–7 MW	–	Surplus energy generated from the solar and wind is stored in pumped hydro and remaining goes to electrolyzer for the production of hydrogen in the proposed HRES for Greek island. The solar and wind supply almost equal energy, which is an indicator of very good complementarity.	[81]
√	√						√			GAMS	COE				GC	H1	NLP	Morocco	50–80 kW	0.1–0.7 $/kW h	Operational strategies and sizing methodologies for storage systems to be used for HRES are evaluated.	[69]

TABLE 4 (*Continued*)

PV	WT	BIO	MH	FPC	BS	FC	PS	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	Social criteria	GC/SA	Architecture	Technique used	Location	Power demand load	Cost	Highlights	Ref.
√			√							MS EXCEL GRG TOOL	COST				GC		MINLP	Poland	11 − 25 kW	–	The feasibility of run of the river pumped hydro storage with PV system for the site in Poland is explored. The fraction coefficient for the amount of power from the grid is optimized.	[70]
√					√					DER-CAM	TAC		CE		GC		DER CAM	USA	3 − 4.6 MW	180 k$ saving per annum	The Distributed Energy Resources Customer Adoption Model employed to size the PV-BS based HRES with a case study of Brookhaven National Laboratory campus.	[80]

Lindo Software is utilized to minimize the cost of energy from the HRES system for Greek Island [84]. For the remote location of Quebec province, Canada, Ibrahim et al. [38] developed the Wind-diesel generator model, which also uses the turbocharger. Pneumatic hybridization of HRES comprising WT, DG and CAES is presented by Basbouse et al. [85] with detailed modeling of IC engine, where the air/fuel ratio is optimized for minimum fuel consumption. CAES is considered in a limestone cavern. Multi-objective linear programming is used to optimize the grid-connected tri-generation plant with PV, DG and boiler by Brandoni et al. [86]. A binary search algorithm is utilized by Ayodele et al. [87] for standalone system in Nigeria with consideration of different seasonal load for the combination of PV, WT and hydrokinetic system.

Table 4 shows the variety of other classical techniques utilized for the optimal configuration of the HRES system. It can be seen that choice of the technique depends on the complexity of the problem formulated and the amount of computational resources, skill-sets and time to be invested in the optimization process. As it is observed, the mixed-integer non-linear programming, codified in suitable software, proves to be the appropriate technique to optimize HRES configuration among classical methods. The HRES system optimization problem is essentially non-linear in nature. That's why non-linear programming techniques have been used for very small systems to up to 50 MW size of HRES system all over the world using a variety of numerical tools.

Modern optimization techniques for HRES sizing

Artificial intelligence techniques try to utilize the principles behind natural biological processes for machine learning purposes. Several techniques have been developed in this area, which try to capture the natural evolutionary and other biological processes mathematically. These techniques do not require large computation time due to their inherent capacity to search for the optima in all the direction with quite a randomness. Apart from that, they can handle many parameters simultaneously, which makes them suitable for multi-objective problems with conflicting objectives [91].

Genetic algorithm

Genetic algorithm utilizes the principle of the survival of the fittest, mimicking the regenerative process followed by the biological species to adapt to their environment. This population-based search technique uses selection, crossover and mutation operators [92] for the enhancement of quality of population in the next generation. The selection operator chooses the individuals in the current population to be maintained for further consideration based on the fitness function criterion. These remaining population members (variable strings) are then brought into the mating pool and crossover takes place, mimicking the combination of DNAs of male and female. These crossed over strings are then mutated randomly. Thus, it processes the population of multiple values of variables in a single iteration of search. It results in search for fairly large search space and improve the average fitness of the population rapidly. The robustness [93] of the genetic algorithm in the handling of the multimodal and non-differentiable objective functions is well-known. The issue of preservation of good solutions during iterations in genetic algorithm simulation is addressed in the improvisation developed like NSGA II [94].

Dufo-Lopez and Bernal-Agustín [95] developed Hybrid Optimization by Genetic Algorithm (HOGA) in C++, which as per their claim, is more nuanced and precise than HOMER in certain aspects. The genetic algorithm is utilized [96] to optimize PV-WT-BS system for telecommunication relay station on the south-east coast of China. Markov model-based GA is utilized for optimization of PV, WT and DG based HRES by Hong and Lian [97], where Fuzzy-c-means is used for uncertainty incorporation. Two sites, one from Germany and the other from Syria, are studied for the installation of HRES using GA in MATLAB/Simulink to minimize the NPV with 10 min interval input data by Merei et al. [98]. PV, WT and BS based HRES is studied for small Greek island by Vrettos and Papathanassiou [99] using the weighted sum method with GA in MATLAB toolbox for minimization of LEC. Ma et al. [100] optimized solar-wind-pumped storage system using LPSP and COE as assessment criteria for the island of Hong Kong using double objective optimization. Due to typhoon sustaining costly wind turbines, the optimal configuration has only one wind turbine. Optimization of HRES with DG is done [101] using a multi-objective system with Monte Carlo simulation. It is emphasized that cost, as well as reliability, is essential criteria for the sizing HRES.

Seeling-Hochmuth [102] has developed a model using a genetic algorithm to optimize the size and operational strategy of HRES with DG using LCC as design criteria. PV, WT and BS HRES system for telecommunication relay station on the south-east coast of China was sized using GA [96] and was constructed for 1.3 kW of AC load and 200 W DC load. The load profile considered is almost constant unlike for the inhabitant usage. Poullikkas et al. [103] employed GA to study the RE penetration in the grid with cost calculation. Gonzalez et al. [104] came up with the algorithm to optimally size the grid-connected PV-WT system using GA for a rural township in Catalonia, Spain. HOGA (Hybrid Optimization by Genetic Algorithms) program is used by Carroquino et al. [105] for the drip irrigation system in the Mediterranean region for least net present cost. They concluded that an energy storage facility other than a battery is required for seasonal energy storage. A genetic algorithm is employed by Al-Shamma and Addoweesh [106] for the sizing of PV-WT-FC-BS-DG based HRES at a rural site in north Saudi Arabia using MATLAB. The results are compared with the HOMER. Tawfiq et al. [107] have employed the iHOGA for the desalination plant in Egypt to overcome the issue of mismatch between load demand and renewable energy supply.

It can be observed from Table 5 that the Genetic Algorithm and its variants remain the most used evolutionary artificial techniques to be employed for the optimal sizing of the HRES. The genetic algorithm finds the global optima with relatively small computation time for the multi-objective and multi-variable optimization problem, which is encountered in the HRES system with multiple energy sources like solar energy, wind energy, bioenergy, hydro energy etc. with different energy storage techniques like battery system, an electrolyzer-hydrogen-fuel cell combination etc. This type of problem may also be evaluated for their environmental impact and social impact. This renders them as the multi-objective problem in addition to multiple decision variables. The versatility of the genetic algorithm and its robustness in finding optimal configuration makes it a suitable candidate to be used for the HRES. As is evident from the research papers reviewed, GA and its variants, especially NSGA-II have gained the confidence of the research community in the HRES field. GA is utilized to optimize the HRES sizes ranging from 300 W to 90 MW for different areas throughout the world, which is the evidence of the capabilities of technique to handle a large variety of problems.

Particle swarm optimization

Particle swarm optimization (PSO) was proposed by Kennedy and Eberhart [120] in 1995 as an alternative to GA and to overcome certain difficulties faced by evolutionary algorithms. It has gained popularity among the researchers ever since. Each variable, called particle, is allowed to move with a certain speed in the space for the search of the best value of that variable. The code also records the global best value for finding out the final solution. The PSO employs the memory aspect [121] of the population of solution variables to avoid the escape of the near-optimal solutions found during the swarm movement. The PSO tries to mimic the certain biological species, which migrate and search for the food in flocks and individual variable of the population is emulated as the member of the swarm [122].

A constrained mixed-integer multiobjective PSO (CMIMOPSO) is presented by Wang and Singh [123] for optimization of grid-connected PV, WT and BS system implemented in C++, where the stochastic nature of wind is also considered. Hakimi and Moghaddas-Tafreshi [124] utilized PSO for optimization of WT and BIO HRES system with Hydrogen as storage career for the village of 2000 people in the south-east coast of Iran. They considered two load scenarios, one of which considers the variable nature of the load. PV, WT, FC and BS based HRES for poly-generation in a small island of Greece is studied using PSO by Kyriakarkos et al. [125] using MS-EXCEL based VBA macro.

Mohammadi et al. [126] optimized the grid-connected PV, WT and BS based HRES for TNPC using PSO. MOPSO is employed [127] for PV, WT, BS and DG based HRES system for COE, LPSP and RF in MATLAB. The HRES system for the site of Uttarakhand state, India is assessed by Upadhyay and Sharma [128] using PSO for EENS, NPC, COE, RF and CO_2 emissions. PV-WT based HRES system is modeled and sized [129] using MATLAB with PSO, where TIC and LOLP are assessment parameters for the location of Riyadh, KSA. The PSO is employed to minimize the levelized cost of energy by Amer et al. [130]. Solar and bio based hybrid system is used to fulfill thermal demand of a town in India by Wagh and Kulkarni [131]. Superiority of dynamic PSO over traditional solvers is demonstrated by Singh et al. [132] with the case of fulfillment of different seasonal loads.

Table 6 indicates that Particle swarm optimization algorithms are at par, if not more, in popularity among the researchers in terms of their usage for the optimal sizing of HRES systems. The number of research publications on optimal sizing of HRES using PSO and its variants is increasing lately. The variants of PSO like Dynamic Multi-objective Particle Swarm Optimization are used by the research community to make it more adaptable to multi-objective HRES problems. It has also been used to compare the results of other algorithms [133]. Part of the reason for its popularity is its ability to arrive at an optimal solution with relative simplicity. From the literature survey, it is observed that the

TABLE 5

Use of GA based algorithms for HRES optimization.

PV	WT	BIO	BS	PS	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	GC/SA	Architecture (BUS)	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√		√		√	MATLAB TOOLBOX	LEC			SA	AC	GA	Greece	307 kW	0.48–0.60 €/kW h	HRES is proposed as a replacement of DG only system for the very small Greek island using the lead-acid battery for energy storage. It was concluded that renewable penetration up to 60 can be achieved without an increase in the cost of the energy.	[99]
√	√		√				NPC			SA		AC	Tunisia	13.35 kW h/day	–	HRES is proposed to be used for the desalination purpose with PV, WT and BS for the site in Tunisia. Five different scenarios with different combinations of the components are considered. Cost of water output is minimized using GA. The results are compared with HOMER.	[108]
√	√		√				TIC	LPSP		SA	H1	Adaptive GA	Taiwan	0.3–1.6 MW	–	Two sites in Taiwan are considered for the case study of HRES optimization using AGA. The results are found to be strongly influenced by the weather pattern of the site.	[109]
√			√		√	MATLAB TOOLBOX	COE			SA	H2	GA	Malaysia	0.5–5 kW	0.24–0.34 $/kW h	Three different combinations of HRES are explored for a rural Malaysian site using GA. The PV-BS-DG comes out to be the most economical.	[110]
√	√		√			MATLAB TOOLBOX	SC			GC	DC	NSGA II	Texas, USA	42–62 kW	1–1.8 M$	Multi-objective optimization of HRES is done using 10-second temporal resolution of power generation and is compared to hourly computation results. It was concluded that higher temporal resolution reflects the nuances of power interaction better and provides a better controllability power flow.	[111]
	√			√			LCOE			GC		GA	Greece	35–90 MW	0.14–0.17 €/kW h	The power supply system of a Greek island is proposed to be augmented with Wind Turbine and pumped hydro storage based HRES. It was concluded at lower RE penetration, this can lead to lower COE.	[112]
√	√		√			MATLAB	LCC	LPSP	EE	SA	DC	Controlled elitist GA	France	300 kW h/ month	LCC $ 32,471	Embodied energy in HRES is also considered as assessment criteria for environment concern in addition to cost and reliability criteria using half-hourly renewable potential data. This study used the variant of NSGA-II.	[113]
√			√		MT	MATLAB TOOLBOX	COE	LLP		SA	H1	GA	Palestine	5–20 kW	0.26–0.39 $/kW h	PV and BS based system is proposed to be augmented by microturbine for Palestinian site, where cycle strategy with co-generation proved to be more economical, although not at par with grid power, if the emission cost and transmission line extension cost is not considered.	[114]

TABLE 5 (*Continued*)

PV	WT	BIO	BS	PS	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	GC/SA	Architecture (BUS)	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√		√		√	MATLAB	COE	LPSP	RF	SA	H1	GA	Saudi Arabia	50–350 kW	0.18–0.23 \$/kW h	Nine different HRES combinations are evaluated for the remote Saudi Arabian village. It was found that the COE increases very fast with RF at high renewable penetration.	[106]
√	√		√		√	HOGA	NPC			SA		GA	Spain	6–20 kW	0.13–1.08 €/kW h	Pumping power requirement of Spanish agrarian use is sought to be fulfilled by the HRES. The irrigation need is mainly in the summer, when wind speed is not high. That's why the optimal configuration has PV, BS and DG, leaving out the WT.	[105]
√	√		√				TC	DPSP		SA		NSGA II	UK	0.5–4 kW	0.01–0.7 M\$ TC	Uncertain input of solar and wind energy is incorporated using chance-constrained programming and compared with Monte-Carlo simulation.	[115]
	√		√		√	MATLAB	Fuel use			SA		GA	UK	0.2–7.8 kW	–	Short term forecast of wind speed and load demand are proposed to be included in the DG operation strategy using GA in MATLAB/Simulink to improve the economics of the HRES and increase the DG lifetime.	[116]
√	√		√				ACS	LPSP		SA	DC	MOGA	Greece	100–1000 W	37.5 k€	HRES for the Greek household is modeled and optimized with multi-criterion methodology.	[117]
√	√		√				ACS	LPSP		SA		GA	China	1500 W	10.6 k\$/yr	Cost and reliability of the HRES are simultaneously optimized including the height of wind turbine and tilt angle of the PV for Hong Kong island.	[118]
√			√		√		NPC			SA	H2	HOGA	Bangladesh	300–1200 W	49k€ NPC	PV-BS-DG based HRES is proposed for the fishermen village in a remote island in Bangladesh.	[119]

TABLE 6

PSO based studies of HRES.

PV	WT	BIO	MH	Tidal	BS	FC	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	GC/SA	Architecture	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
	√	√				√				NPC	ELF		SA		PSO	Iran	220–800 kW	43.85 M$	Different types of loads like residential, industrial, agricultural and office load are considered with different reliability needs. The increase in the load in the future is also forecasted and the increase in the PV, WT and FC capacity is suggested along with the life of the project.	[134]
√	√				√	√		√	C++	TCS	UL	CE	SA		ε constraint PSO	Spain	0.4–4.4 kW	95–140 k€	Multiobjective optimization is carried out using ε-constraint PSO coupled with simulation module and sensitivity analysis is also performed for HRES with hydrogen production and utilization system for energy storage mechanism in addition to the battery.	[135]
√	√				√			√		LCOE	PRSP	SCC	SA		PSO	India	70 kW	0.41–0.62 $/kW h	A case study of the site in India is performed to find out an optimum mix of resources of HRES. PV, WT and BS was found better economically using dual reliability constraint test.	[136]
√	√				√	√		√	C++	NPC	UL	CE	SA		DMOPSO	Spain	0.4–4.4 kW	57–165 k€	Dynamic multi-objective PSO is demonstrated for the optimization of HRES with a case study of Spanish site. The results are compared with MOGA, MOPSO and ε constraint method. The CO_2 emission is also considered as the assessment parameter.	[137]
√	√				√				MATLAB	LCC	LPSP		SA	DC	Adaptive inertia based PSO	Iran	0.5–4.7 kW	68 k$	Five variants of PSO are applied for HRES optimization for the site in Iran. Adaptive inertia weight-based PSO comes out to be better among them with minimum life cycle cost comprising PV, WT and BS.	[138]
√						√			MATLAB	NPC, COE		CE	SA	DC	PSO	Australia	3.5 kW h/day	25–65 k$	HRES to feed load demand along with desalination requirement of potable water is optimized using multi-objective PSO (including cost and emission) for west Australian site and is compared with HOMER analysis.	[139]

TABLE 6 (*Continued*)

PV	WT	BIO	MH	Tidal	BS	FC	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	GC/SA	Architecture	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√								C++	NPC	LLP	CE	SA		DMOPSO	Canada	10–100 MWh / month	500–1000 k $	Sampling average method with synthetic data generation is used to incorporate uncertainties in the solar, wind and load data for the multi-objective optimization of HRES. A case study of a building in Canada is performed for the minimization of renewable fraction, emission and cost.	[140]
√	√	√					TS		C++	NPC		CE, RER	GC		DMOPSO	Canada	10–100 MWh/ month	383–957 k$	HRES for power, heating and electric vehicle of the apartment building in Canada is analyzed using DMOPSO. PV panels, solar collector and heat pump don't show up in the optimized solution, which is dominated by wind turbine, heat storage and biomass boiler.	[141]
√	√				√					LCOE		RP		H2	iPSO	Singapore	0.4–1.2 MW	0.29 $/kW h	HRES for the tropical climate is optimized for different renewable penetration levels using distributed mutated PSO and is benchmarked against standard PSO and intermediate mutated PSO.	[142]
√	√				√				MATLAB	TA			SA	DC	PSO	Iran	2–7.5 kW	9.5 k$	Monte Carlo simulation is utilized to incorporate the uncertainty in wind speed and solar radiation along with PSO to optimize the HRES for the site in Iran.	[143]
√	√				√			√	MATLAB	NPV	EIR	CE	GC	IEEE-69	i-MOPSO	Spain	9.22 kW h/day	45 k$	Three objective optimization of HRES using PSO with non-dominated Pareto front is presented for the site in Spain. The DG size is not considered for optimization.	[144]
√					√			√	MATLAB	ACS	LLP	CE	SA	H2	PSO	Algeria	0.5–2 kW	17.4 k$	HRES for the site in Algeria is sized using PSO for cost, reliability and environment criteria. Results are compared with HOMER results. DG required for the months with low solar radiation availability.	[145]
√	√				√			√		COE	LPSP	RF	SA	AC	MOPSO	Sweden	2–2.8 kW	0.24 $/kWh	Twelve locations in rural Sweden are studied for the HRES including the PV, WT, BS and DG using MOPSO. It is noted that high renewable fraction can be achieved with a varying range of LPSP even for these very high latitude sites.	[146]

TABLE 7

Artificial intelligence techniques used for HRES optimization other than GA and PSO.

PV	WT	BIO	MH	BS	FC	PS	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	Social criteria	GC/SA	Architecture	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√					√			C++	TC	DSR			SA		Evolutionary algorithm	Greece	500 kW	2.07 €/m^3 of RO water	Evolutionary algorithm-based code is employed to simulate the desalination plant run by solar, wind and pumped storage combination. The optimal system gives the economic potable water with a substantial waste of renewable energy.	[150]
√							CAES SC		OPTQUEST	TC				GC		SD-AB	USA	10–75 MW	–	System dynamics and agent-based code is developed for optimal size and operation of HRES with broad analysis at the national level and detailed work for the local conditions. The solar radiation is presumed to resemble historical data with January and Jun as base months for the case study of a site in Arizona, USA.	[167]
√	√								MATLAB, simulation in PSCAD-EMTDC	COE	LPSP			SA	H1	ANFIS	Malaysia	0.5–5 kW	11.5 k$	Adaptive Neuro-Fuzzy Inference System is employed to optimize the HRES for the site of Malaysia, where validation is performed using PSCAD.	[151]
√	√			√				√	C++	LEC	ULF			SA	DC	Evolutionary algorithm	Sri Lanka	3.5–7.5 kW	0.3–0.6 $/kWh	DG integrated HRES for the Sri Lankan site is optimized using an evolutionary algorithm for levelized energy cost and unmet load factor. It was observed that additional DG capacity reduces storage requirement with better reliability.	[168]
√	√			√				√		LEC	ULF	WRE		SA	DC	MOEA	Sri Lanka	3.5–7.5 kW	0.32–1.04 $/kWh	Multi-objective steady ε-state evolutionary algorithm is utilized to optimize four objectives of HRES. MCDM is utilized to shortlist the components from the pareto front by Fuzzy TOPSIS.	[169]

TABLE 7 (*Continued*)

PV	WT	BIO	MH	BS	FC	PS	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	Social criteria	GC/SA	Architecture	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√								MATLAB	TAC				SA		DHS	Iran	1.1–2.9 kW	7.2 k$	Discrete Harmony Search method is presented for the optimization of HRES, which can effectively handle discrete variable like no of wind turbine. This algorithm can produce results in a very short time.	[153]
√	√			√				√		LCE, ICC		GHG		SA	DC	ε-state evolutionary algorithm	Sri Lanka	3.5–7.5 kW	0.25–0.45 $/kWh	Steady ε-State Evolutionary Algorithm is utilized to get pareto front of the three objectives for HRES namely Levelized energy cost, initial capital cost and greenhouse gas emissions. The case study of the site in Sri Lanka is presented.	[170]
√	√									TC	EENS			SA		Pattern search	USA	–	6.7–10.6 M $	Autoregressive moving average method is used to consider uncertainty in solar and wind resources and demand load. Pattern search in combination with sequential Monte Carlo simulation method is employed to optimize the system cost and reliability.	[154]
√	√			√				√		ACS	LPSP	Fuel emission		SA		PICEA	Spain	23–55 kW	3–11 k$	Preference inspired co-evolutionary algorithm with goal vectors is utilized to optimize the HREs for a rural site in Spain. The slope angle of the photovoltaic panel and the hub height of wind turbine are also found along with the size of component for optimal cost, reliability and emission.	[152]
√	√			√					MATLAB	TAC	LPSP			SA	DC	ABSO	Iran	2–7.5 kW	56 k$	PSO, TS, IPSO, IHS, IHSBSA and Artificial Bee simulation optimization are applied to optimize the HRES for the site in Iran. The ABSO gives better results in comparison to other techniques used.	[155]
√	√							√	A-STRONG	ETC						Simulation optimization	Taiwan	–	–	A stochastic trust-region response surface method in combination with Monte Carlo Simulation is proposed to be used to size the HRES. The results are compared with simulated annealing and Nelder-Mead simplex method.	[171]

TABLE 7 (*Continued*)

PV	WT	BIO	MH	BS	FC	PS	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	Social criteria	GC/SA	Architecture	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√			√				√	MATLAB	COE	EENS LLP			SA		BBO	India	52–180 kW	0.15 $/kWh	Wind and solar resources used for the optimization of HRES are based on the forecasted data from an artificial neural network trained by back propagated code. The sizing is optimized using biogeography based optimization method for the case of the site in India.	[156]
√	√									TLCC, LCOE				SA		Heuristic Algorithm	Nicaragua	1.75 kW	0.838 $/kWh	The Greedy Randomized Adaptive Search Procedure is used to size the HRES for the Nicaraguan site for a small rural community with detailed wind flow analysis.	[157]
√	√			√					VB.net in MATLAB	TC				SA	AC	ACO	Iran	1.2–2.9 kW	6.7 k$	Ant colony optimization with continuous domains is deployed for HRES design for the site in Iran. The simulation results are compared with GA ABC and Branch & Bound method.	[158]
√	√			√				√		NPC			HDI, JC	SA	AC	MOEA	Sahrawi refugee camps, Tindouf	1–14 kW	0.21–0.56 $/kWh	Multi-objective evolutionary algorithm is presented for the pareto front of HRES to minimize the net present cost human development index and job creation for the refugee camp in Africa. Photovoltaic control is proposed to be achieved by a secondary code, which uses genetic algorithm.	[160]
√	√				√				MATLAB	LCC	LPSP			SA	DC	ABSO	Iran	2.2–5.5 kW	3.8–8.4 M$	The potable water along using reverse osmosis with power load requirement is proposed to be met by the HRES using hydrogen as a storage medium for the site in Iran. The system is optimized using artificial bee swarm optimization for different reliability levels.	[161]
√	√			√					MATLAB	TSC	LOLE EENS			SA	H1	Cuckoo Search	India	3–21 kW	10 k$	Cost and reliability of HRES for the site in the Uttarakhand state of India is optimized using the cuckoo search with levy flights. The results prove to better than GA and PSO.	[172]

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TABLE 7 (*Continued*)

PV	WT	BIO	MH	BS	FC	PS	Other storage	DG	Tool used	Economic criteria	Reliability criteria	Environment criteria	Social criteria	GC/SA	Architecture	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√		√							MATLAB	TNPC	LPSP			SA	H2	Harmony search	Iran	30−210 kW	0.186 $/kWh	The HRES to supply power for agricultural needs of irrigation is optimized using harmony search for the site in South Iran. Biomass gas-based generator is added to HRES, which proves to be better than PV alone system.	[163]
√	√			√	√			MT		Cost of Electricity				SA	H2	Flower pollination algorithm	China	200−980 kW	3.9−4.1 M$	Assimilation of EV charging infrastructure in HRES microgrid for three different scenarios is studied. Flower pollination algorithm is used to optimize the energy scheduling and point estimate method & support vector machine are used to count for Stochastic probabilities.	[173]

coding PSO algorithm is generally done using MATLAB or C++. PSO is utilized to optimize the HRES of various capacities of up to MW scale as evident from the literature surveyed.

Other evolutionary algorithm

The classical techniques of optimization generally use the gradient information to determine the search direction or some search technique [147] with certain conditions to determine the path and direction to follow during the process. These techniques generally bring in a single value of decision variables to optimize the mono-objective problem. The evolutionary algorithm techniques are a step apart from them in the sense that they evaluate multiple values of decision variables in the form of population. This ensures the possibility of getting good diversity in the decision variable outcomes in addition to the optimal value for the multi-objective problems [148]. The following passages summarize the use of evolutionary algorithms other than GA and PSO for the optimal configuration of HRES.

Ananostoplous and Papantonis [149] designed the wind-based hybrid system with a hydro-power pumping station as storage. Simulations are done for a one-year duration with a frequency of 10 min. Three different types of pump configurations are tested and the variable speed pump system is proved as most cost-competitive. The desalination system using PV, WT and PS is optimized [150] using EA based software by the National Technical University of Athens. It was observed at that time that a reduction in the cost of PV can lead to economics in favor of these type of systems. ANFIS (Adaptive Neuro-Fuzzy Inference System) is presented for the PV and WT based HRES by Rajkumar et al. [151] in MATLAB. They used the Gaussian membership function to back propagate the data and results are compared with the HOMER and HOGA.

Preference inspired co-evolutionary algorithm (PICEA) is suggested for the least ACS and LPSP for the location of Spain by Shi et al. [152] and has been validated through simulation. The results are also compared with GA & PSO. Discrete harmony search (DHS) is utilized by Askarzadeh [153] for the minimum total annualized cost in MATLAB for the site of Iran. Sequential Monte Carlo Simulation is proposed [154] to calculate the reliability along with pattern search method for the optimization of PV-WT system and Autoregressive Moving Average Method is used to include the uncertainty in input data. PV, WT and BS based HRES is optimized by Maleki and Pourfayaz [155] several evolutionary algorithms for TAC and LPSP in MATLAB, where ABSO was found robust among studied algorithms. Biogeography based optimization is executed by Gupta et al. [156] PV-WT-DG-BS based HRES for given EENS in MATLAB and Artificial neural network (ANN) is used for forecasting of wind and solar potential. A heuristic algorithm is employed by Ranaboldo et al. [157] for the site of Nicaragua, where the type and number of WT and PV panels are optimized. Fetanat and Khorasaninejad [158] proposed ACO with integer programming for PV, WT and BS based HRES optimization to minimize the total cost of the system. The results are compared with the ABC, GA and B&B.

Singh et al. [159] used ABC for the PV-WT-BIO-BS HRES system optimization in MATLAB for a site near Patiala, India. The results were compared with HOMER and PSO. The multi-objective evolutionary algorithm is employed by Dufo-Lopez et al. [160] for

TABLE 8

Hybrid techniques employed for the HRES optimization.

PV	WT	BIO	BS	FC	PS	DG	Other source	Tool used	Economic criteria	Reliability criteria	Environment Criteria	GC/SA	Architecture	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√	√	√	√		√			COE	UL		SA		SA + TS	Greece	120 kW	0.2 €/kWh	Simulated annealing is used to derive the feasible solution, which is fed to Tabu search. The Tabu search has an inherent capability of descent gradient, which makes this hybrid technique potent to be used.	[180]
√	√					√		MATLAB	NPV			SA		PSO and QP	Iran	1.5–5 MW	22–2 M$	Quadratic program finds the optimal dispatch management strategy for least net present value. Then, PSO finds optimal sizes of components of HRES.	[181]
√	√			√				CIPLEX	IC			GC		Heuristic preselection and superstructure	Croatia	0.2–1.8 MW	26 M€	HRES for Croatian island is studied with hybrid optimization. The stochastic heuristic technique is employed at the initial stage. The remaining search space is screened by the super structure-based method. This gives better results with less time in comparison to conventional techniques.	[182]
√	√								Cost					Modified Cuckoo Search & differential algorithm	Iran	–	10 k$	Cuckoo search is modified by making Levis flight dynamic along with a differential algorithm to make it capable of creating pareto front for the HRES.	[183]
√	√		√					Fluent for tilt angle	PBT	LPSP		SA		Flower pollination algorithm and Simulated Annealing	Iran	0.35–2.25 kW	12–14 years	Hybrid method combining flower pollination simulated annealing is used for the HRES of three flour building in Iranian capital city. The tilt angle of the PV panel is optimized using for the wind turbine using computational fluid dynamics.	[176]
	√			√			GT	MATLAB	Cost	Power Loss	CE	SA		ACO + ABC	Iran	3.7 MW	–	Artificial bee colony algorithm is used to search the location HRES and ant colony optimization for the sizing of the components. The point estimation method is employed to incorporate the uncertainty in the wind speed.	[177]

TABLE 8 (*Continued*)

PV	WT	BIO	BS	FC	PS	DG	Other source	Tool used	Economic criteria	Reliability criteria	Environment Criteria	GC/SA	Architecture	Optimization technique used	Location	Power demand load	Cost	Highlights	Ref.
√	√							MATLAB	COE				IEEE-33	GA + PSO	Canada	3–3.7 MW	–	HRES for power load and electric vehicle charging infrastructure integrated is considered for the optimization for the smart grid. The strength of PSO and GA in floating number and integer numbers respectively are exploited to optimize this integrated system.	[184]

assessment of net present cost, human development index and job creation with HRES based on PV-WT-BS-DG for the refugee camp in Algeria, Africa. Life cycle cost of PV, WT and FC system with LPSP OF 0%–10% is studied using Artificial Bees swarm algorithm [161] in MATLAB. Cuckoo search is used to optimize PV, WT and BS based stand-alone HRES for total system cost and energy expected and not supplied in the MATLAB [162]. The results are compared with the GA and PSO. Heydari and Askarzadeh [163] proposed the harmony search for the optimization of PV-BIO HRES with LPSP and TNPC as assessment criteria in the MATLAB for agriculture wells in Iran. PV and BIO based [164] HRES with AC-bus are optimized using ABC for hourly performance for the site near Patiala, India and the results are compared with HOMER. HRES based on PV, WT, BS and DG is studied using Taboo search [165] for minimization of COE in MATLAB. Differential evolution and chaos theory based methodology for the optimal operation of hybrid plants is reported by Mandal and Mandal [166].

As is evident from Table 7, a variety of evolutionary algorithms other than GA and PSO are employed for the HRES design and optimization. Simulated annealing, harmony search, flower pollination algorithm are among them. There is a clear trend of novel techniques being implemented in this field. It is due to the rise in the number of research efforts as the field of the evolutionary algorithm itself, which is evolving very fast aided by allied fields of computer sciences. Evolutionary algorithms are being employed to optimize HRES sizing by the researchers especially in developing countries as evident from the literature survey. Remote areas of India, China and Iran including Greek islands are considered for the case studies using these techniques. Researchers are increasingly looking for applications other than electric power consumption for the HRES. The areas like electric vehicle integration in HRES microgrids are emerging fields to explore as per the latest trends in publications on HRES optimization.

Hybrid techniques

The classical techniques are better in finding local optimal values, as they generally move in the direction of local gradient in search space. The meta-heuristic techniques are better in converging towards global optima, because of their population based search in addition to go-everywhere approach. The relative strengths of conventional and artificial techniques can be combined by applying them together in sequence. Initially, the population based random search technique narrows down the search space as per its characteristic relatively easily. These results are fed as input to the conventional technique to zero in at the optimal value. This type of augmentation, which combines two types of optimization processes, to improve the robustness of optimization process is called the hybrid techniques. Following is the brief of research done on the optimal configuration of HRES using hybrid techniques.

Rentizelas et al. [174] developed a decision support system for multi biomass system used for multi-purposes including heating and cooling requirements along with power production in Greece. This system uses a hybrid algorithm, which has a genetic algorithm (GA) as the first step and sequential quadratic programming (SQL) as the second. The HRES system combining the PV, WT and BS for Auckland, New Zealand [175] for zero LPSP using a newly presented hybrid optimization technique consisting of GA and exhaustive search technique. A hybrid approach using Flower Pollination Algorithm and Simulated Annealing for given LPSP is presented by Tahani et al. [176] for PV, WT and BS system, where the effect of wind speed, for the given tilt angle of the PV panel, is studied using CFD analysis in FLUENT. The hybrid optimization technique combining Ant Colony Optimization and Artificial Bee Colony is proposed [177] for Wind based HRES, where uncertainty is incorporated using the point estimation method using MATLAB. CSAHS (Chaotic simulated annealing-based harmony search) and SAHS (Simulated annealing-based harmony search) [178] are employed for the PV, WT and FC system in MATLAB for the location in Iran, where SAHS is found to be better. Carapelluci and Giordano [179] simulated the code for the farm in central Italy using Genetic Algorithm — Simulated Annealing algorithm with hydrogen (H) as energy storage carrier. They examined three configurations, namely, PV-H, WT-H and MHP-H separately with MHP-H as concluded more economic.

Several attempts to find a good combination of more than one search technique can be seen in the literature surveyed as summarized in Table 8. It is important to maintain the relative merits of individual techniques while combining them together. The amalgamation of classical techniques with heuristic technique is widely implemented as seen from the literature reviewed. Although there was one study noted, which combined GA and PSO, to get the benefit of their strengths in floating and integer numbers respectively. Researchers especially from Iran have tried to come up with hybrid techniques to deploy for HRES optimization as evident from the literature survey. Authors see a lot of opportunities for further research in the quest for further inquiry in the field of HRES optimal design and sizing.

Conclusions and discussion

A comprehensive review of optimization techniques used for the optimal configuration of hybrid renewable energy systems (HRES) is presented. The shortcomings of the conventional optimization techniques like their inability to handle a large number of variables and mono-objective model restricted them to earlier use. In the early days of the evolution of the HRES, the economics and reliability criteria were the focus of the designers of the HRES system. Nowadays other criteria like the carbon emission for environmental concerns and job creation in the social sphere are increasingly seen as assessment parameters. This makes the modeling of HRES much more nuanced and adds subjectivity in the selection of design solutions among the Pareto optimal results of the multi-objective optimization problem. Artificial techniques like genetic algorithm (GA), particle swarm optimization (PSO) and other evolutionary algorithms are needed to effectively handle multi-criteria decision-making. Various variants of GA and PSO have been employed for the HRES sizing optimization to customize the algorithms as per the need of the HRES sizing problem. Many of the researchers tried to combine two different optimization techniques to use the advantages of both, which seems to be the way forward for the researchers working in this area. The feasibility studies of HRES of GW scale for the grid supply seems to be way forward. The HRES of the scale of kW and double-digit MW have been considered until now. The feasibility studies of HRES of GW scale for the grid supply need to be considered. The research community is expected to put efforts into the development of modeling and optimization tools to deal with that.

The combination of solar, wind and biomass is a promising combination in the regions, where a sufficient amount of biomass is available, as it can minimize the economic cost of battery system type energy storage and environmental cost of diesel generator type dispatchable source. The energy storage techniques other than battery storage like electrolyzer-hydrogen-fuel cell combination for HRES need to be further explored. In addition to that, the HRES is progressively considered in the grid-connected mode. In the early days, the cost of energy from HRES was more in comparison to grid-supplied power, so HRES were considered mainly for remote locations and islands in stand-alone mode. In the context of increasing environmental cost and steady decline in the cost of renewable energy power extraction technologies has led to consider HRES system increasingly in grid-connected mode. This has made the AC bus-based or special purpose hybrid bus-based architecture of HRES imperative.

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