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Optimization in microgrids with hybrid energy systems – A review

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ABSTRACT

Fast depleting fossil fuels and the growing awareness for environmental protection have led us to the energy crisis. Hence, efforts are being made by researchers to investigate new ways to extract energy from renewable sources. 'Microgrids' with Distributed Generators (DG) are being implemented with renewable energy systems. Optimization methods justify the cost of investment of a microgrid by enabling economic and reliable utilization of the resources. This paper strives to bring to light the concept of Hybrid Renewable Energy Systems (HRES) and state of art application of optimization tools and techniques to microgrids, integrating renewable energies. With an extensive literature survey on HRES, a framework of diverse objectives has been outlined for which optimization approaches were applied to empower the microgrid. A review of modelling and applications of renewable energy generation and storage sources is also presented.

Contents

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1. Introduction

Microgrids combine different energy sources in the best possible manner to cater to local loads with the ability to operate either connected or disconnected with the utility grid. They can be viewed as a controllable subsystem generating power from the Distributed Energy Resources (DER) which are mostly renewable in nature. The microgrids were first developed by the Consortium for Electric Reliability Technology Solutions (CERTS). They have, in the recent past, enhanced the flexibility of the power systems by improving the reliability of the power delivery. Microgrid, though it has been in discussion lately, is an old concept. If we notice the early developments of the electrical industry, all power systems have been isolated. The world's first public power station was a steam-powered electricity generating station initiated by Thomas Edison in London in the years and later at Manhattan in 1882. He proposed the generation of power locally using DC generators, but there were no means available for conversion of voltage to the desired levels. Microgrids share a lot of similarities with these early systems as they too are generated locally with dedicated loads. Hence we state that the early isolation strategies are now revisited in the form of microgrids which have the distinct capability of incorporating grid connections as and when necessary.

Extreme centralization has led to a lot of drawbacks such as limitations on the use of non-renewable fuels, expansion of existing networks, reducing congestion on existing lines and threats from malicious entities. An entire nation's communication to infrastructure; utilities to even defence depend on its electric power. Hence, pooling of the entire control of power in one place makes it an attractive target for malicious attacks. These factors combined with an inclination to promote the use of renewable energy have led the development of distribution generation. The concept of having the DER allows the decentralization of the power generation and the storage. In fact, the definition for DER includes both the generators and the energy storage technologies. The generation facilities are called Distributed Generators (DG) and they include a small power generating units which may be placed at an isolated site not connected to the power grid or the site of the customer [1]. The microgrid is connected to the utility grid through a Point of Common Coupling (PCC). Microgrids provide a good platform to realize the DGs to harness the green energy. Since they can be viewed as a subsystem of power generation and associated loads, their local control is easier, thus eliminating the expensive costs and hazards of central dispatch centres. DGs include much electricity generating technologies of which some are the conventional internal combustion (IC) engines and gas turbines. Whereas, the other renewable systems like photovoltaics, wind turbines and fuel-cells are also included. Some renewable sources are capable of generating a DC voltage and hence they have to be interfaced with the AC distribution system using the power electronic interfaces. They have many significant advantages such as lower maintenance costs, emissions and higher reliability and flexibility. Hence DGs find many applications other than power generation, such as acting as backup sources and deferrals for upgrades in transmission and distribution systems [2].

Yet, without optimal utilization of sources the cost of investment for a microgrid shall not be justified. Optimization is to find the best alternative of a set of given solutions which is most cost-effective or has the highest achievable performance under the given constraints. Hence optimization tools, techniques and applications are the most sought after topics for research in the recent times. An attempt to summarise the importance of optimization especially in the field of microgrids with hybrid power sources is presented. This paper also provides an overview of the various hybrid microgrid systems currently being explored and the various optimization methods and applications that are being employed. While attempts have been made at summarizing optimization tools [3] and methods [4] to hybrid systems, this paper is novel in the sense it entails an account of various objectives in diverse power system applications targeted for optimizing the HRES. The paper is structured as follows. The evolution of microgrids and the importance of optimization are briefed in Section 1. In Section 2, Hybrid Renewable Energy Systems (HRES) are introduced and a brief discussion followed by a review on the modelling of various energy sources viz. – Solar, Wind, Diesel generators and Energy Storage Systems (ESS) is presented. Section 3 gives an approximate classification of the application areas for optimization in microgrids. Objectives of optimization in the HRES are presented, taking into account the trivial factors such as minimization of costs, emissions and price arbitrages in Section 4. Section 5 lists the various tools and techniques employed to perform optimization. The reviews conclude with an overall discussion on potential areas of development and future research.

2. Hybrid renewable energy systems (HRES)

Our planet houses enough power generating resources to cover its ever growing demand for electricity. But the power generated from some of these sources is intermittent or not of required power quality owing to their stochastic nature. Hence a complete transition from fuel based generation to renewable generation society will need a non-single combination of these alternating energies. Alternative energy sources like hydro, geothermal, biomass, wind, solar, hydrogen, nuclear and fossil fuels need to be made to work together in different combinations as a single unit to meet a common demand area. The term HRES describes a system having different DGs integrated to power the customer's demand. HRES can be a combination of conventional sources like, diesel generators and/or renewable sources like photovoltaics (PV) and wind turbine (WT) exploited in various combinations with storage systems as shown in Fig. 1.

Remote areas providing hardships for laying of new transmission lines are ideal areas where HRES can be implemented to ensure cost-effective and reliable delivery of power. Alternative sources of energies are in wide use in developing the HRES systems all around the world. They are also being installed to generate power in large scales. Renewables like solar and wind energies depend on climatic conditions. Hence they are very difficult to predict and impossible to control. However integrating two or more resources that can compensate the drawbacks of one another has found to overcome this problem. The idea is to use the strengths and disadvantages of one source to counterbalance those of the other. But there is now a new difficulty in analysing these integrated systems due to the complexity of the combining sources. Hence a lot of research is done in finding the solutions for optimum utilization of renewable sources to promote green energy. Sizing, operation and control of the renewable sources in an HRES are very essential for its techno-economical feasibility and stability [5,6].

Of the above mentioned energy technologies hydro, biomass combustion and geothermal power form the first-generation technologies which have been in use since the end of 19th century industrial revolution. Solar heating, wind power, bioenergy and photovoltaics belong to the second generation technologies which emerged in late 90s through R&D. The oil crisis of 1970s created the awareness of the depletion of fossil fuels prompting investment in alternate sources. But a growing concern for environmental protection has sustained the development of the renewable green energy. Further development has introduced the third-generation technologies which include biomass, geothermal and ocean energies. Their development and implementation

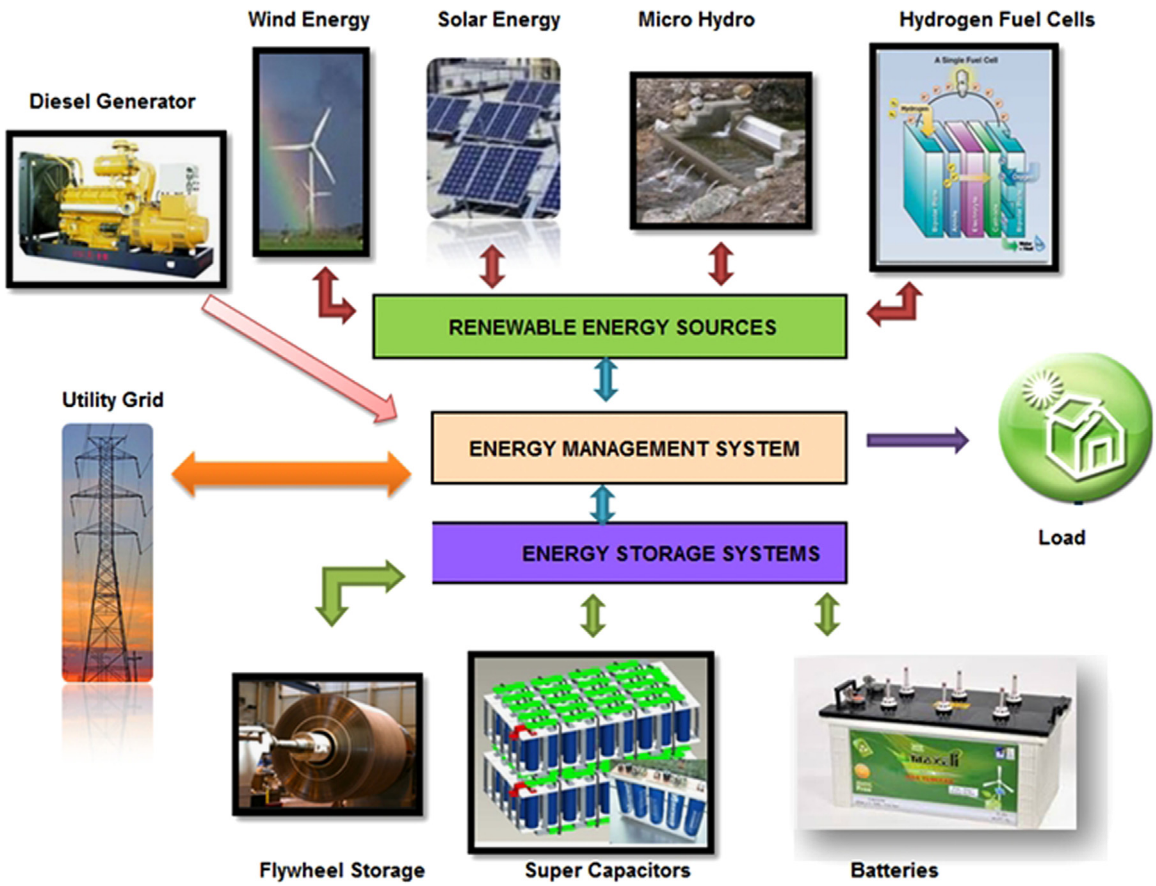

Fig. 1. Hybrid renewable energy sytems.

Table 1
India's energy sources and their contribution to the total power (as on 28-2-2014).

Type of source	Generation capacity in MW	Percentage
Coal	140723.39	59.19
Gas	21381.85	8.99
Oil	1199.75	0.50
Hydro (Renewable)	40195.4	16.91
Nuclear	4780	2.01
RES	29462.55	12.39
Total	237742.94	100

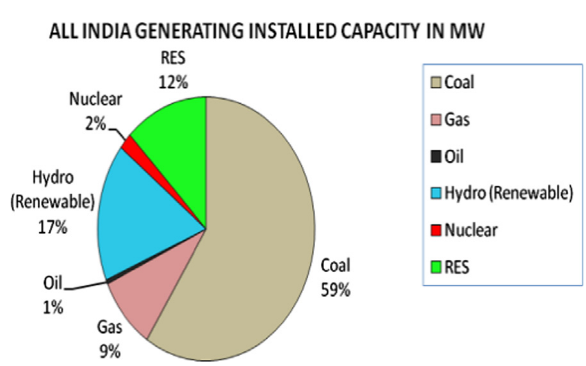

Fig. 2. India's energy generating sources and their contribution.

are further aided by the advancement in the field of nanotechnology [7–9]. An estimate of the contribution of renewable sources to power generation in India is given as in Table 1. (As on 28-2-2014 Source:CEA). 12% of India's power is generated by renewables of which about 70% of power comes from wind energy conversion systems. An illustration is shown as Fig. 2.

This paper concentrates mostly on the systems integrating solar, wind, diesel and energy storage systems. Solar and wind systems have been on the increase all over the globe to produce electric power in the past decade. This is because they are abundant in nature, clean and site-dependent. Also, owing to very low maintenance costs, they are highly cost-effective. These advantages have been attracting power researchers and investors alike. A brief overview of the renewable energy sources and their modelling is outlined below. Banosa et al. [10], gave a detailed analysis on various research works carried in various alternative energies. Many researchers have attempted to model the various renewable systems. But a complete study of each is not in the scope of this paper. However studies by Zhou et al. [11,12], Deshmukh and Deshmukh [6] and Bajpai et al. [13] provide a review of research papers on the modelling of the renewable energy systems. The studies clearly point out that a combination of PV and Wind energy generation is growing increasingly popular owing to their complementary nature. Luna-Rubio et al. gave an overview on sizing methodologies considering hybrid energy metrics like LPSP, SOC, LCE, etc. [14]. These system metrics are explained further on in this paper. Many other papers which explain modelling of the hybrid sources have also been included in this section [5,6,15–20].

2.1. Solar energy

Solar energy is the energy radiated by the sun, which is harnessed by tapping light photons to generate electrons. Solar energy is now generated on a large scale with many energy investing companies promoting it. But it needs a lot of expertise for implementation, site designing and development. Indian states like Gujarat and Rajasthan are harnessing solar energy, thus completely utilizing their geographical position. Other states are also following suit to realise their solar potentials by reviewing their solar policies. The PV system consists of a photovoltaic array which converts the light photons falling on it to electrons. This generates a DC current which can be boosted with DC–DC converters and then inverted to deliver AC power to the loads. Thus, power electronic devices form an important part in interfacing the PV to the grid. Also, a specific Maximum Power Point Tracking System (MPPT) is employed to enable the PV to extract maximum energy from the sun by altering the slanting angle of its rays all through the day. At last, the power is filtered with a low-pass filter to eliminate unwanted harmonics before it enters the grid.

All PV cells are mostly made of semiconductor crystalline materials. There are many types of PV cells as mono-crystalline, poly-crystalline and thin-film PV cells. New advancements in cell production technology have brought on the introduction of titanium-oxide coated PV cells which highly improves the output efficiency. The PV cells are grouped to form modules which can then be electrically connected in series and/or in parallel forming large units with scaled voltages and increased power outputs. An MPPT system is most important for optimal absorption of solar energy to maximize the efficiency of the conversion system. Though the solar insolation may vary naturally through the day, the MPPT system adjusts the PV array output to generate maximum real power at a constant voltage. Reactive power control is done using an inverter controller operating in constant power factor mode. A silicon PV module output depends on many variable including the type of material, temperature and solar radiance incident on the surface of the module. Its output can be expressed as

$$P_{pv} = P_{STC}\frac{G_c}{G_{STC}}[1 + k(T_c - T_{STC})] \tag{1}$$

where P_{pv} is the output power of PV module in watts, $GSTC$ is solar irradiance in W/m^2, T is the temperature in °C, GC is the irradiance of operating point, k is the power temperature coefficient, $PSTC$ is the rated output generated by the module under standard test conditions in watts [5]. T_c can be calculated using the following expression:

$$T_c = T_a + \frac{(NOCT - 20)}{0.8}G \tag{2}$$

where T_a is ambient temperature (in °C), G is the global solar radiation incident on a horizontal plane (in kW/m^2) and $NOCT$ is the Normal Operating Cell Temperature, which is approximately 48 °C. Considering that the PV modules are connected in series and in parallel as explained before to increase the output voltage and current. A matrix of N_S X N_P PV modules is modelled here where N_S is the number of series connected modules and N_P indicates the no.of modules connected in parallel. The output voltage and power of the PV system is given as

$$V_{PVA} = N_{PVS}V_{PV} \tag{3}$$

$$P_{PV} = N_P N_S P_{module}\eta_{MPPT}\eta_{oth} \tag{4}$$

where η_{MPPT} is the efficiency of the MPPT system and η_{oth} is the factor which represents cable resistance and other losses [15]. The local observatories usually provide data on solar irradiance as incident on a horizontal plane. Hence Hongxing et al. [16] employed the Perez model which helps to find the solar irradiance data for slanting planes with the aim to exploit maximum η at any time.

2.2. Wind energy

Wind is the most promising source of alternate energy. Though USA and China are the fastest growing wind power countries in the world, European countries are the actual leaders. Germany and Spain have the highest installed wind generation capacity of the world. India has started developing wind power from the early 90s and it now boasts of housing the fifth largest wind power installation in the world. Even though our country is relatively a newcomer when compared to Denmark and USA, the Indian wind industry has increased significantly in the past decade. India ranked first in the growth rate of wind power generation in the world during the year 2009–2010. The state of Tamil Nadu generating more than 7000 MW is the leading state contributing to about 40% of India's wind power. It is rightfully deemed as a wind power hub of South Asia. The power (energy/second) available in the wind will be given by the formula

$$\text{Power} = 0.5A\rho V^3 C_p \tag{5}$$

where A is the rotor swept area in m^2, ρ is the air density in kg/m^3, V is the average wind velocity in (m/s) and C_p is the power coefficient, which is a function of tip-speed ratio and rotor mechanical speed. It can be noted that the power generated is proportional to the cube of the wind velocity, hence a small difference in wind speed can effectively create a large difference in the available energy and the cost of generation. Wind turbines have a lifespan of about 20 years. They are most effectively used in groups known as 'wind farms' or 'wind power plants' with capacities varying from a few megawatts to few hundred megawatts in capacity. Though wind farms are spread over a large geographical area, their actual "footprint" covers only a very small portion of the land. Thus, a vast area of land is available to farmers to earn additional revenue, thereby revitalizing the economy of the rural communities.

The development of wind power has encouraged the development of turbines and auxiliary equipment. Due to extensive research in this field in the recent past there has been an increase in size of turbine and reduction in the prize of installation. Limitations found are low speed of the wind thereby making siting and prediction procedures to be of vital importance. Wind energy potential depends on operation scheme, wind speed estimation, site selection for farms, etc. However primary interest for researchers also lies in optimal design of wind farms including design of wind turbine and layout of farms [10]. The difficulty in setting up more wind farms is the unavailability of wind forecast data as compared to solar forecast data. This is because solar energy is comparatively more predictable than wind energy. Hence siting of wind parks is a highly important aspect which involves huge efforts to conduct studies and analysis of wind in that area. Wind Energy Conversion Systems (WECS) convert wind energy to electrical energy in two steps – First a turbine converts the wind power to mechanical torque which then rotates a generator to produce an electric current. WECS maybe classified as fixed speed and variable speed systems. Double-Fed Induction Generators (DFIG) and Permanent Magnet Synchronous Generators (PMSG) are the most outstanding technologies in use for the variable-speed WT's. The WT maybe connected to the generators through a gear-box and capacitor banks are provided as DC links. Further, converters are used to economically invert the DC power generated and for compensation and interconnection purposes. Power control is implemented at various stages of the WECS. Mechanically the torque generated by the WT can be controlled by pitch angle control of the turbine blades. The electric power generated by the DFIGs can be controlled using bidirectional power converters interfaced between the rotor windings and the grid. They are usually constructed with two IGBT bridges linked back-to-back with a capacitor provided in between to serve as the DC link.

The expression for output power of a wind turbine can be related to wind speed with the following function [5]:

$$P_{wt}(v) = \begin{cases} 0, & v \le vci \quad \text{or} \quad v \ge vco \\ \frac{P_{rated-wt}(v - v_{ci})}{(vr - vci)}, & vci \le v \le vr \\ P_{rated-wt}, & vr \le v \le vco \end{cases} \tag{6}$$

where v_{ci}, v_{co} and v_r are cut-in, cut-off and rated wind speeds respectively. $P_{rated\text{-}wt}$ is the rated output power of the WT. Final output $P_{out} \le P_{wt}(v)$ due to losses. The output power of wind turbine can always be adjusted to match the load demand. Qi et al. [18] categorized the operation of WT unit into three states depending on the load demand and operating wind speeds. When load exceeds generated power, the WT is operated in Maximum Power Point Tracking (MPPT) state. The system is operated under rated wind speed to capture efficient wind energy. Whereas at times when load is lesser than the power generated, WT is said to be in load power tracking control state. Here the generator speed is controlled so that the system now generates only as much energy, as to satisfy the load demand and charge the battery storage if necessary. At high wind speeds, exceeding v_r, the WT operates in over speed protection state. So that, the speed of rotation is controlled and, therefore, prevents any harm to the electrical unit of the system. There are always limitations which one must consider in order to operate the WT safely and within reasonable speed limits. Dump loads are very handy in preventing over speeding of the WT.

Modelling for wind generation is briefed in some of the papers studied [5,6,15,17,19,20]. Sarrias et al. gave a detailed modelling of the DFIG and its power converter and thereby analysed the controller performance for optimal energy management [21]. Zhao et al. [22], modelled a DFIG wind turbine which took into consideration distribution network reconfiguration with effective reactive power control. Particle Swarm Optimization (PSO) algorithm was used to minimize the system real power losses and voltage deviations, subject to operating constraints.

2.3. Diesel generators

To promote green energy, diesel generators are now mostly used only as backup resources in HRES. In the case of the renewable sources and battery systems failing to supply the load, diesel generators are brought into action. There are many deciding factors for the choice of diesel generators including types of load, fuel costs, transportation costs, etc. [23]. Deshmukh and Deshmukh considered a sizing problem of engine generator under two conditions – one when the diesel generator is tied to the load directly and another when it is used as a battery charger [6]. Overall efficiency of the diesel generator can be expressed as

$$\eta_{overall} = \eta_{brake\ thermal} \times \eta_{generator} \tag{7}$$

where $\eta_{brake\ thermal}$ is brake thermal efficiency of diesel engine. Operation of the generator at 70–90% of full load is found to be economical. Diesel generators are, thus helpful in boosting power during peak demand hours and later for energizing the energy storage units as and when required. Power limits for diesel generators can be expressed as

$$k_{gen} P_{rated-gen} \le P_{gen} \le P_{rated-gen} \tag{8}$$

The value of k_{gen} is set to 0.3 based on the manufacturers' suggestion of the Dongfushan island system [5].

2.4. Energy storage sytems

The most prominent disadvantage of renewable sources, unlike their conventional counterparts is that they cannot be stored for later use. Hence, the need to extract maximum energy from them during their limited availability is of utmost importance. Moreover, they cannot be ensured to be ever consistent and concentrated as they tend to depend upon the climatic conditions of the site. This makes them very irregular and unreliable. Due to the highly unpredictable behaviour of wind, the power generated by WT is highly prone to harmonic distortions and related errors which can harm the system operation. ESS is needed in such conditions to even out the irregularities and improve the power quality. ESS is also essential for controlling the power outputs and providing ancillary services as and when required. Thus, they are an indispensable source of energy to achieve high penetration of renewable systems. Any power imbalance between the load and the generation units can be counterbalanced with ESS acting as buffer or back-up. A microgrid working in islanded mode will depend on ESS for real and reactive power balance arising due to possible malfunction of some DGs. Even if the problem is met by load shedding or starting up other generating units, ESS is critical for providing the interim power shortfall almost instantaneously [24–26]. While the MG is operating in grid-connected mode ESS are necessary to maintain the power quality and to regulate the reactive power. Francisco Díaz-Gonzáleza et al. gave a complete review of the various storage systems and their applications [27]. Listed below are some ESS which have currently found usage in microgrids with HRES.

1. *Pumped Hydro Storage (PHS)*: is a hydro-power storage which stores water in two reservoirs maintained at different heights so that, the potential in water as it flows from higher to a lower reservoir can generate power. At periods when demand is low the water is pumped back to the higher reservoir and stored there for later usage. It is the most simple and widely practiced energy storage scheme (99% of all ESS) all over the world [28].
2. *Battery Energy Storage Systems (BESS):* are the most popular of all ESS currently in use. They store energy as a charge in electrochemical cells. The desired capacity and voltage can be achieved by connecting them in series or parallel or both. The four principal types of batteries are lead–acid, nickel–cadmium (Ni–Cd), sodium–sulphur (NaS) and lithium-ion (Li-ion) batteries. Each type of battery has its own advantages and disadvantages. Lead–acid batteries are the cheapest of all but Sodium–sulphur batteries have the highest energy density of 151 kW h/m^3 [24]. Ni–Cd batteries render potential advantages like longer cycle life and nickel metal hydride batteries are more environment-friendly. Li-ion batteries are the costliest of all but give high energy densities. Hence depending on the type of application the type which is most suitable is selected. The complete account of various batteries can be seen from Table 2.
3. *Compressed Air Energy Storage (CAES):* systems store atmospheric air in underground caverns under high pressure. When this compressed air is made to pass through special heaters they are combusted with natural gas and allowed to expand and they release immense amount of energy. This resulting energy drives a turbine which generates electricity, which is fed to the grid. Research work is progressing in this area to improve the efficiency of the system by finding ways to store and use the heat energy released during the process (Adiabatic CAES). This heat when used to heat up the air before the combustion process can save fuel costs. This technology is being explored in Germany [27–29].
4. *Flow Battery Energy Storage System (FBESS):* have liquid electrolytes stored separately and are pumped into the battery whenever required. They are rechargeable batteries having long life cycles

Table 2
Analysis of various ESS and their applications.

S. No	Energy storage technology	Lifetime	Cost in ($/kW h)	Efficiency (%)	Short term power supply	Arbitrage and peak shaving	Unit commitment	Power quality improvement	Ancillary services
1	Pumped hydro storage (PHS)	**30–50 years**	**500–1500**	**65–75**	✓	✓	✓		✓
2	Compressed air energy storage (CAES)	**40 years**	**100–350**	**71**	✓	✓	✓		
3	Lead–acid battery	**5–15 years**	**150–1300**	**75–90**	✓	✓			
4	Nickel–cadmium battery (Ni–Cd)	> **3500 cycles**	**150–1300**	**90**	✓	✓		✓	
5	Sodium–sulphur battery (NaS)	**2000 cycles**	**450**	**85**	✓	✓		✓	
6	Lithium-ion battery (Li-ion)	**3500 cycles**	**150–1300**	**85**	✓	✓		✓	
7	Vanadium redox flow battery (VRB)	**15–20 years**	**150–1300**	**75–85**	✓	✓		✓	
8	Zinc–bromine flow battery (ZBB)	**20 years**	**150–500**	**75–85**	✓	✓		✓	
9	Polysulphide bromide flow battery(PSB)	> **15 years**	**150–1300**	**75**	✓	✓		✓	
10	Hydrogen-based energy storage system (HESS)	> **20 years**	**800–1200**	**42**	✓	✓	✓		✓
11	Flywheel energy storage system (FESS)	> **20,000 cycles**	**380–2500**	**90**	✓			✓	
12	Superconducting magnetic energy storage (SMES)	> **50,000 cycles**	**Very high**	**90**	✓			✓	
13	Super capacitor energy storage system	> **5 times 10000–100000 cycles**	**250–350**	**75–95**				✓	

and very low maintenance costs. The liquid electrolytes which carry positive and negative charges respectively are separated by a selective membrane. There are three types of FBESS namely Vanadium Redox Battery (VRB), Zinc–Bromine Battery (ZBB) and Polysulphide Bromide Battery (PSB). A number of chemical reactions like oxidation and reduction occur among electrolytes inside the battery, thus giving its name as redox flow batteries [30].

5. *Hydrogen-based Energy Storage System (HESS).* Electrical energy is stored by electrolyzing water to produce hydrogen and oxygen. For grid energy storage applications the hydrogen is then passed through a fuel cell that recombines the hydrogen with oxygen thereby producing an electric current. This system is therefore also known as Regenerative Fuel Cell (RFC). The main components of the HESS involve a water electrolyzer system to electrolyze water, a fuel cell stack, provision for storing the Hydrogen generated and a power electronic interface for power quality. The system is very simple and advantageous as it is completely emission free but the only disadvantage is its low efficiency (42%). Since a single fuel cell can produce voltages less than 1 V we need a stack of RFC to scale the output voltage to desired values thereby increasing the investment costs [31].
6. *Flywheel Energy Storage Systems (FESS):* use the mechanical inertia of a rotating flywheel in order to store energy. Flywheels use a motor/generator set to first drive a flywheel accelerating it to high speeds and saving electrical energy in the form of rotating kinetic energy. When the stored energy needs to be retrieved, the motor acts as a brake extracting energy from the rotating flywheel. Energy that can be stored in the flywheel is found to be proportional to the square of the rotating speed and its inertia. Their ability to rapidly charge and discharge is suitable for applications in improving power quality. High efficiency, energy density and long lifetime [32].
7. *Superconducting Magnetic Energy Storage (SMES):* systems generate strong magnetic fields within a superconducting coil and store energy in the form of an electro-magnetic field. The energy stored hence is expressed as LI^2 where L is the inductance of the coil and I stand for the current value. As can be seen, this value is not affected by the rate of discharge as opposed to other storage systems hence they retain energy for a longer period of time. Niobium–Titanium is now used in most SMES. They are capable of storing large energies from 100 kW to 10 MW, and are characterized by rapid power injection capabilities. They are most suitable for application in improvement of power quality and have infinite life cycle [24,33].
8. *Super Capacitor Energy Storage Systems* or ultra-capacitors or electric double layer capacitors (EDLC) store energy in the electrostatic form between the capacitor plates. They are capable of storing and discharging a large amount of charge in a very short time. Thus they are very helpful in applications of frequency and power quality improvement. Advances in material sciences have suggested that when activated carbon electrodes are used in super capacitors they can be expected to store charge of up to 10^3 times per unit volume. They have 0% maintenance and high efficiencies [24,34].

The various benefits of ESS in microgrids are listed below [24,27]:

1. *Short Term Power Supply, Spinning Reserve*: When a microgrid is switched to operate in islanded mode then the power shortfall due to the disconnection of the external grid needs to be compensated instantaneously. ESS can provide this power so that the mode transfer may appear to be seamless and smooth. At times when any of the DGs fail due to faulty conditions the ESS come into picture acting as a buffered source to meet critical customers. Different ESS systems can be combined to act as a single source unit capable of storing energy during excess generation and giving it back when generation is deficient. These features of ESS have helped the penetration of renewables in the microgrid thereby creating a spinning reserve.
2. *Peak Shaving or Time Shifting*: ESS is made to store the renewable energy generated at off-peak demand times during which the utility power supplies the load, as it will be cheaper. Then, at peak demand times when the price of the utility power is more, the ESS is discharged to meet load or even sell the stored power back to the utility. This avoids the start-up costs of conventional sources as the peak demand is now reduced and

further saving cheap power and selling it at peak times is a profitable idea.

3. *Optimization of microsource for Unit Commitment*: ESS can be used to solve problems relating to unit commitment services. ESS capable of storing energy for longer time periods extending up to some days may be considered for this application.
4. *Power Quality Improvement*: Power generated by renewable sources like wind power is very erratic and prone to fast output fluctuations causing network frequency variation, thus affecting its power quality. Power quality is very important for sensitive loads such as chip technologies and automated manufacturing. Sensitive loads like these have risen to 40% of total load, and are expected to increase to more than 60% by 2015. Voltage control of wind power plants at the point of common coupling to withstand transient voltage dips (known as Low Voltage Ride Through) up to even 0% of the rated voltage is essential to prevent collapsing of network. In order to mitigate these effects an ESS can be used. HRES are also required to mitigate power oscillations of the system by absorbing or injecting active power at frequencies of 0.5–1 Hz. Many storage technologies are suitable for this service.
5. *Ancillary Services and Seasonal Storage:* Ancillary services include load following, operational reserve and frequency regulation applications. Large scale power plants or PHS are used for providing ancillary services. Hence ESS which can store and discharge power for longer time frames is used. ESS which have very less to no self-discharge and avoid losses are preferable for these applications.

Batteries are undisputedly more widely used in the current scenario. However Flywheels are also fast developing. SMES and super capacitors are seeing more research work as of now. A complete analysis of ESS and their applications is given in Table 2. Xiao et al. suggested a two-level combined energy storage mode to meet the short term storage (with super capacitors) and long-term energy storage (with Li-ion battery or VRB) requirement for wind power [35].

Model of Battery source: An example of modelling of a lead–acid battery storage system is given here. At any given time, there are some limitations for the SOC of the lead–acid battery system which can be expressed as

$$SOC_{\min} \le SOC_t \le SOC_{\max} \tag{9}$$

where $SOC_{\max}$ is the upper limit, and SOC_{min} is the lower limit SOC for the battery. Similarly limits for the output power of the lead–acid battery can be expressed as

$$P_{cha-max} \le P_{bat} \le P_{discha-max} \tag{10}$$

Where $P_{cha-max}$ and $P_{discha-max}$ are the maximum-allowed charging and discharging power for the battery, P_{bat} is positive when discharging, and negative for charging. The SOC value at time $t+\Delta t$ is related to SOC value at time t by the following equation:

$$SOC_{t+\Delta t} = SOC_t - \frac{P_{bat,t} \times \Delta t}{C_{bat}} \tag{11}$$

$P_{bat,t}$ is the battery power during the sampling period; and C_{bat} gives the battery charge capacity. The charging efficiency and discharging efficiency are both assumed to be 90%, according to the practical situation of the Dongfushan Island system [5].

Today we are able to generate only less than 20% of the volumetric capacity from batteries [36]. Hence there is wide scope for improvement in terms of performance as well as in topologies and materials. BESS technology is a fast growing area where there is vast opportunity to harness the power extracted from renewable sources. In spite of its poor efficiency hydrogen storage systems will become competitive in the near future due to increasing fossil fuel prices and reduced lifetime of BESS. Similarly all other energy storages are also seeing rapid increase in research and development to improve overall efficiency of stored energy both economically and in an eco-friendly manner.

2.5. System metrics

These system metrics form the crux for optimizing the HRES as they are the performance indicators of the reliability and/or feasibility of the system. This helps system designers to size up the system components adequately. Some of these metrics have been listed here [14].

Annualized Capital Cost (C_{acap}) forms a major part of Annualized Cost of System (ACS) of each component (PV array, wind turbine, battery and wind turbine tower) and is given as

$$C_{acap} = C_{cap} CRF(i, Y_{proj}) = C_{cap} \frac{i(1+i)^{Y_{proj}}}{(1+i)^{Y_{proj}} - 1} \tag{12}$$

$$\mathrm{ACS} = C_{acap} + C_{arep} + C_{amain} \tag{13}$$

where C_{cap}, C_{arep} and C_{amain} are the initial capital cost, annual replacement cost and annual maintenance cost of each component respectively; Y_{proj} – lifetime of each component in years; CRF is the capital recovery factor and 'i' is related to the nominal interest rate. CRF can be defined as ratio to calculate the present value of an annuity (a series of equal annual cash flows). Also referred to as Total Annualized Cost (TAC) of the system.

Loss of Power Supply Probability (LPSP) is an important metric indicating reliability of the system. It can be defined as the ratio of total energy not supplied (deficit) to the total load demand over a given time period.

$$LPSP = \frac{\sum_{t=1}^{T} DE(t)}{\sum_{t=1}^{T} P_{load}(t)\Delta t} \tag{14}$$

where $DE(t)$ is the deficit energy at hour t. P_{load} is the load demand for period T etc.

Levelized cost of energy (LCE) is the price per unit of energy and is calculated as ratio of the total cost of system taken annually i.e. TAC of system to the total energy delivered during the same period by the system (E_{tot}) [14].

$$LCE = \frac{TAC}{E_{tot}} \tag{15}$$

Battery's State Of Charge ($SOC(t)$) of a battery gives an account of the energy stored in the ESS at a sampling time t and can be calculated with the expression given below

$$SOC(t+1) = SOC(t)\sigma + I_{bat}(t)\Delta t \eta(I_{bat}(t)) \tag{16}$$

Where σ is the self-discharging rate of battery bank, $I_{bat(t)}$ is the current for charging, Δt is the time period per sample, and $\eta(\mathrm{I}_{bat(t)})$ is the efficiency of charging current.

Expected Energy Not Supplied ($EENS$) is a probabilistic index to measure the reliability of the system. When load exceeds availability in the energy system $EENS$ gives a measure of the expected energy that was not supplied. For electrical load (L), and power generated by HRES (Ph), $EENS$ can be calculated as follows:

$$EENS(L, P_h) = \begin{cases} L - \int_{P_{h\ \min}}^{P_{h\ \max}} P_h f P_h(P_h) dP_h & L > P_{h\ \max} \\ \int_{P_{h\ \min}}^{L} (L - Ph) f P_h(P_h) dP_h & P_{h\ \min} \le L \le P_{h\ \max} \\ 0 & L < P_{h\ \min} \end{cases} \tag{17}$$

where $f_{Ph}(P_h)$ is the probability density function of power generated, $P_{h\ \max}$ is the maximum power generated, $P_{h\ \min}$ is the minimum energy generated by the HRES. Other metrics like energy payback, balance of plant, simple payback time, cost of saved energy and the avoided costs of CO_2, NO_x etc. are also used [15,37,38].

3. Applications of optimization

Optimization may be applied at any point in the microgrid to achieve the best operating conditions while meeting all the necessary constraints. Setting up of a microgrid, its operation, maintenance and scheduling activities involve various decision making situations that call for the application areas for optimization. In mathematics, an optimization problem is defined as a problem to find the most optimal solution from a set of feasible solutions. For easier analysis the application areas for optimizing hybrid microgrids has been roughly segregated into three categories such as generation side, control side and distribution side.

Designing of an HRES requires an exhaustive analysis on deciding the perfect mix of generating and storage systems as per requirements. In such situations optimization tools and techniques have been employed by designers extensively [39–44]. Optimization may also be applied to decide upon the best possible solution for the sizing and siting strategies for DGs. A sizing problem deals with the kind and capacity of the generators that can be employed to achieve the predetermined results, confirming that it meets all the necessary constraints in the best possible manner. Whereas, siting deals with the problem of the placement of these generators on the distribution bus (as long transmission is not characteristic of microgrids) so as to minimize the transmission losses and to deliver the maximum quality power to the load. Many research works have been done in this field by applying various optimization methods [45–47].

Operation or control management of a microgrid provides a vast complex decision making area where optimization may be applied to deliver reliable and the best quality power to the customers while safeguarding the grid at all times. It plays an important role to ensure the stable operation of a microgrid economically. They also balance the energy management between the generation, load and storage. It also strives to obtain optimal use of the available renewable sources of energy to ensure maximum overall efficiency. Dagdougui et al. [48] proposed a real-time mathematical optimal solution for control management of a hybrid system integrating hydropower, wind power and fuel cells. The case study is based in Afourar village, in Morocco. The most significant decision is to decide the operating modes of the microgrid i.e., whether to stay connected with the utility grid or to operate as an islanded entity at any given point of time. Also about the microgrid operation and the power needed to be controlled during the change of operating modes. Control methods employed in microgrids are roughly categorized into primary, secondary and tertiary levels. Primary droop control is the most fundamental control to balance the voltage and the frequency shared between the load and the grid. Errors like steady-state errors which are not eliminated in primary control are controlled in the secondary levels [49]. Tertiary control is responsible for the decision making regarding the energy exchange and the peak shaving between the microgrid and the utility grid. Dasgupta et al. [50] discusses a hardware communication less control mechanism for interchanging operating modes of a microgrid system. Hassan and Abido analyzed the operation of the microgrid by optimizing controller parameters, power sharing co-efficient and damping resistance. The grid was studied during both states as to connect or not to connect to the utility grid and also under load variations [43]. Al-Saedi et al. [51] analyzed power quality enhancement when the grid is switched from interconnected to islanding mode of operation and during the load change. A real-time self tuning of power controller parameters for voltage source inverter-based DG was also presented to ensure minimum ITAE (Integral Time Absolute Error) while sharing power equally with the utility grid [52] under dynamic and steady state responses [53].

On the distribution side, the major tasks of scheduling demand tracking and optimal energy management provide a significant area of research. Baziar [54] proposed a probabilistic framework based on 2 m Point Estimate Method (2 m PEM) to consider the uncertainties in the optimal energy management of the Micro-Girds (MGs) including different renewable power sources. Scheduling and dispatching of the generated power while minimizing the emission costs were discussed in [55] and [56]. While the former work used niching evolutionary algorithm to minimize the operating cost and emissions, the latter used the differential evolutionary algorithm for heat balancing in a Combined Heat Power (CHP) based microgrid. A complete mathematical analysis of smart microgrid characteristics for developing a novel economic dispatch using a hybrid genetic algorithm is done by Liao [57].

4. Optimization objectives in HRES

4.1. Designing objectives with ESS

The initial cost of setting up a solar or wind energy system is higher than diesel engine generator of comparable size, but the operating and maintenance costs are always lower than that for a diesel engine generator. Energy storages can smoothen out the mismatch between the time of occurrence of peak demand and the generation. So the match of power generating sources for setting up of an HRES is purely a designer's problem of optimization with many constraints to be met. Reliability and costs need to be balanced in the design strategies. Many dynamic factors like the site location, uncertainties and quality requirements of the many renewable systems in an HRES have an influence on the decision strategies [41]. In a recent study, supply security related aspects were also considered in designing the microgrid structure by defining a probability adequacy index [44].

Energy storage systems have now become an integral part of an HRES with renewable systems as explained before. The selection of energy system depends heavily on economic evaluation metrics such as energy price arbitrage, reducing transmission access cost, deferring facility investment, the investment costs, the operating and maintenance costs, energy costs, power costs, balance of plant costs, efficiency and lifetime [5,58–65]. Leou [58] considered installation costs, operation and maintenance expenses and revenues including energy price arbitrage for reducing transmission access costs and deferring facility investment. Genetic algorithm with linear program (GALP) was used in the paper to determine the optimal capacity and operations of a VRB energy storage system. Sundararagavan [66] gave a cost analysis of eleven types of energy storage technologies for key applications associated with a wind farm integrated into the electric grid, including load shifting, frequency support and power quality. Chedid et al. [60] provided the core of Computer Aided Assessment tool that can help designers to determine the optimal design of a hybrid wind-solar power system for either autonomous or grid-linked applications with diesel generators and battery backups. The proposed analysis employed linear programming techniques to minimize the average production cost of electricity while meeting the load requirements in a reliable manner. A survey on various efforts to optimize energy storage systems in HRES has been elaborated below.

Batteries have been most commonly used in hybrid systems due to their low cost and easy availability. Tewari et al. [67] analyzed a NaS battery system for shifting power generation from off-peak to on-peak and ramp rate limiting to smoothen the wind output. Also, an optimized siting strategy for the NaS batteries was detailed based on market prices. Khalid [68] developed a new semi-distributed scheme which effectively minimizes the BESS capacity required, using model predictive control theory thereby reducing the overall cost of the system. Brekken et al. [69] used flow batteries to manage the uncertainties in wind output with an Artificial Neural Network (ANN) strategy to further lower energy costs. Sizing and control methodologies for a ZBB based energy storage system were also presented. Hydrogen systems though inefficient are being used with battery systems in HRES. Sharafi et al. [42] combined an optimization method (PSO algorithm) with a simulation tool like ε-constraint and the hybrid method was used to model the HRES. A sensitivity analysis conducted in the study proved that reduced lifetime of batteries increases the costs. Thereby, an optimal configuration could opt for hydrogen storages rather than batteries even though they are inefficient. Giannakoudis et al. [70] analysed the uncertainties existing in an HRES integrating PV–Wind–Diesel and hydrogen based ESS. A stochastic design approach is proposed which uses a stochastic annealing optimization algorithm to handle the increased combinational complexity. Vosen [71] investigated a solar-battery-hydrogen storage energy system with two different control algorithms. One was a traditional approach based on SOC of the battery and the other was an advanced neural network algorithm which was evaluated based on costs for energy storage. The results indicated that the battery-hydrogen hybrid system storage costs 48% of the cost of a hydrogen-only system and only 9% of the cost of conventional, battery-only system. On the contrary, Katsigiannis compared lead–acid batteries and hydrogen storage systems based on LCE and emissions using NSGA-II optimization and found that hydrogen-based system showed an increase in both LCE and emissions as compared to the lead–acid based system [65]. This was due to high electric storage cost and increased fuel consumption of the diesel generator. A local search procedure with multi-objective genetic algorithm was proposed which combined the excellent quality and the wide range of non-dominated solutions, while decreasing the computational time. Etxeberria [59] compared by means of simulating 3 topologies used to control an ESS formed by a super capacitor bank and VRB.

Choi [72] attempted optimization of a battery/supercapacitor hybrid ESS for reducing battery charging current fluctuations and energy losses in supercapacitors. Thounthong et al. [73] proposed a novel concept for integrating a supercapacitor with a PV–FC hybrid power plant to operate as an auxiliary source and a short-term storage system. Using fuzzy-logic controller for DC grid voltage regulation, the transient behaviour of the system during load changes is studied. Based on a case study conducted by Prodromidis [74], micro-hydro-wind systems were found to be the optimal combination for the electrification of the rural villages in Western Ghats (Kerala) India. Nine different Renewable Energy System (RES)-based scenarios were compared and simulated in which three used electrochemical batteries as the backup energy and six were a combination of electrochemical batteries and flywheel systems. It was observed that although the initial costs of systems with simple batteries are much lower, systems combining flywheels can be competitive because the NPC of the different systems is equivalent. Similarly, Hafez et al. [75] compared four systems based on LCE, where environmental emissions are also taken into account. Both the above comparative studies were performed with HOMER software. Large scale storage systems like PHS and CAES are also being considered in HRES designing. The main difficulty in integrating these systems is that they are site dependent and have a long gestation period. Raya [76] showed that costs were slightly higher for CAES system but for high power applications they were recommended as the batteries were found to be inefficient and polluting. Kahrobaee and Asgarpoor[77] developed a model for wind-CAES system and applied a PSO technique to optimize the day-to-day operation and long-term planning of system with the objective of maximizing the profits.

Thus, optimization techniques have been extensively applied for effective utilization of energy storage systems in the design process. They are mostly analyzed based on economic metrics and performance parameters. However effect of market prices and demand uncertainties on optimal design configuration still need to be explored for different energy storage systems.

4.2. Sizing objectives

In order to efficiently and economically utilize renewable energy resources, the optimum sizing of generating units is very important. The sizing optimization methods can help to guarantee the lowest investment with a reasonable and full use of the HRES components. This ensures that the system can work at the with optimal configurations in terms of investment and reliability requirement of the demand load with a cleaner environment. Many researchers have written review papers on the sizing methodologies adopted for optimal designing of HRES. Most common objectives considered for optimal sizing of an HRES are economic and environmental objectives. Nehrir et al. [78] of special task force of the IEEE PES Renewable Energy Technologies subcommittee under the energy development and power generation committee analyzed different approaches for system configuration, unit sizing, control and energy management of hybrid systems under research. Details of HRES projects developing all over the world were also summarized. Bernal-Agustı´n et al. [79] and Zhou [11] have also presented their reviews on designing, simulating and control of the HRES using PV and/or wind and/or diesel with battery storages. Luna-Rubio gave an overview of sizing methodologies with various indicators optimized to achieve maximum performance at minimum cost [14]. Elma and Selamogullari [20] analyzed a stand-alone hybrid system (PV/Wind/Backup) that supplied electrical needs of a stand-alone residential house. It was found that for optimal backup sizing, high resolution load data, wind speed and solar radiation data must be used as compared to the use of hourly averaged data found in conventional literature. This proved that when load and source dynamics are considered, approximately 10% less backup size was needed.

Economic system metrics like the ACS, LPSP, LCE and fuel costs have been considered for sizing in many studies. Hongxing developed and analyzed a hybrid solar-wind-battery system optimized model for minimizing cost of the system (ACS) with LPSP as major constraint [15,16]. Ekren [80] studied the sizing problem for a PV/Wind/BESS system to be installed in a GSM station, in Turkey. The sizing problem was solved using Response Surface Methodology (RSM) and a minimum energy cost of $37033.9 was acheived. By comparing this energy cost to transmission line costs (for transmission lines to be set up from GSM station to proposed HRES site) through break-even analysis, a siting strategy was also developed [81]. Further application of Simulated Annealing (SA) algorithm for fast convergence, resulted in a 10.13% reduction in energy costs [82]. The authors propose to expand the study to inspect the effect of dynamic auxiliary energy unit costs on optimum total costs and investment costs. Katsigiannis et al. [83] also adopted SA with tabu search algorithm to reduce the LCE thereby increasing system efficiency. The hybrid algorithm used yielded an 80% success rate with a minimum cost of 0.1946 €/kW h.

Multi-objective optimization techniques are also gaining usage in sizing problems. In Ref. [84], a triple multi-objective optimization method to help designers to take into consideration both economic and environmental aspects was attempted using a controlled elitist genetic algorithm. The objective function combined Life Cycle Cost (LCC), Embodied Energy (EE) and LPSP metrics. In such cases, the solution is a multitude pareto front. The results proved that LCC and EE of the system are correlated and for less than 5% LPSP a minimum LCC of $32471 needs to be endured. A differently nested approach was demonstrated by Di-Silvestre et al. [85] for a multiobjective optimal operation. An inner optimization procedure for unit commitment used NSGA-II algorithm aimed at minimizing the cost and maximizing profits. The external procedure chooses the design features such as ratings and/or types of DGs by implementing a glow-worm swarm algorithm aimed at minimizing costs and emissions. In Ref. [86], a combined multi-objective optimization and a multi-criterion decision making technique followed up with decision support tools based on fuzzy TOPSIS and level diagrams for designing of HRES. Four different objectives, i.e., LCE, unmet load fraction, wasted renewable energy and fuel consumption are used to obtain the Pareto front. Arnette [87] developed a multi-objective linear programming model for planning of an HRES enabling the decision maker to design the system balancing generation costs and emissions under various operating scenarios. Hence, considering the sizing objectives individually the wind and solar potential capacities were evaluated.

Market prices of fuels also affect the operating costs of HRES. Hence some researchers have attempted to analyze their effect on the design process of HRES systems. Zhang et al. [88] proposed a novel method for optimizing power dispatch simulations in a PV–battery–Deisel system by minimizing LCE which also considers fuel cost, emission's damage cost, capital depreciation cost and maintenance cost. The results indicated that LCE is sensitive to fuel prices and as demands grow the replacement charges of batteries involved will also rise. This study clearly points out that even though investment cost on PV was higher the capital cost of batteries outgrows it through the lifetime of the system. Perera et al. [89] designed a standalone HRES considering LEC, capital costs and green house gas emissions as objectives in the sizing methodology. Market and reliability analysis is conducted on the system to prove that reduction of fuel prices improves the LEC-emission pareto front due to integration of renewables in the system.

The above mentioned studies mostly included the economic and environmental objectives. Tan et al. [90] proposed a novel optimization problem for siting and sizing of DGs considering technical aspects such as real power losses, the voltage profile, the grid VA requirement, etc. The methodology combined PSO and gravitational search algorithm (GSA) to handle the mixed non-linear nature of the problem. However costs are not considered in this study. Imran et al. [91] presented a new approach for siting and sizing of DGs for minimizing network power losses, operational costs and improved voltage stability. These studies inspect sizing of DGs in common and hence are free of uncertainties involved with renewable sources. Hence there is still scope for combining technical and economic indicators proposed in these sizing methodologies to different renewable systems with their investment costs and uncertainties.

4.3. HRES control and energy management

Optimization techniques play a major role in the operation of an HRES to achieve the desired quality power at predetermined costs. Optimization can be applied to any part of the HRES. Generation controls like MPPT control systems, operation controls for power quality and cost control, energy management decision making controls and control of power dispatch are the major application areas for optimization. Some examples of state of art in control and management are listed below.

4.3.1. Power quality and cost control

Power quality is improved by power conditioning devices like statcom and quality control strategies in the distribution systems [51,52,92]. Their optimal placement and implementation is very improtant to reduce costs and enhance performance [93]. Serban [61] designed an original hardware-in-the loop (HIL) solution for real-time testing and optimization of the frequency control mechanism in autonomous microgrids, where battery energy storage systems (BESS) were integrated along with classical RES generators. Sigrist [62] assessed the economic benefit of primary frequency regulation reserve and peak-shaving generation in small isolated power systems by including an ESS thereby achieving a total cost reduction of 23.2 Mio €/year with an internal rate of return of 7.25%. Vrettos et al. [63] considered penetration of WT-ESS to an existing Diesel unit in Agios Efstratios, Greece. Using GA to optimize the LCE for the hybrid system it was concluded that, with 75% RES penetration level, a 10–15% of reduction of LCE could be achieved. On the same concept for a similar HRES microgrid (PV–WT–BESS and DG in Dougfushan Island) in 2013 Zhao [5] considered the lifetime characteristics of lead–acid batteries while performing multiobjective optimization to minimize power generation cost and to maximize the useful life of lead–acid batteries. It was proved that a higher RES penetration level can lead to a significant reduction in overall costs about 30%. Younsi et al. [94] developed a supervisory control to determine the energy transfer type of FESS integrated with a wind–diesel system. The objectives of the control are to satisfy the power requested by AC grid, to manage the energy transfer between hybrid system and AC grid, to optimize the use of wind energy, and to reduce fuel costs of diesel generator. Arabali et al. [95] used GA to a hybrid system catering to a single HVAC load and analyzed the cost and efficiency of operation under various conditions. Modified ε-constraint method was used to solve the multi-objective optimization problem to minimize total operation cost and emissions. Introduction of commercial power system simulators have made a study of power flow controls in a microgrid much easier with the help of powerful analytical and visualization tools [96,97].

4.3.2. Power dispatch control

Optimization techniques find increasing usage in power system applications like economic dispatch, unit commitment and generation scheduling. Conti et al. [56] proposed an optimization procedure to enable optimal dispatch of DGs and ESS in a medium-voltage islanded microgrid aimed at minimizing operating cost and emissions. Zhang et al. [98] suggested a novel power scheduling approach for minimizing generation and storage costs, utility costs of dispatchable loads and worst-case transaction cost due to uncertainties of renewable sources. CHP, when included in an HRES, greatly improves the efficiency and justifies the investment costs. In Ref. [64], a CHP-based DG microgrid comprising ESS with three types of thermal power generation units and Demand Response Programs (DRPs) was analyzed. Maa et al. [99] also explored CHP generation field by conducting a feasibility study on a residential microgrid system comprising hybrid PV–WT and CHP generator. The performance and dynamics of the system due to the combined environmental condition changes and electrical faults were addressed. Zhang at al. [88] proposed sizing and control of an HRES based on the optimization of the power dispatch simulations. Minimization of the LCE with consideration to the capital depreciation cost, fuel cost, emissions damage cost and maintenance cost was aimed at. More recent approaches use commercial simulators like PowerWorld for power dispatching problems [96]. It makes investigations and analysis including complex market policies much simpler. Parisio et al. implemented model predictive control for optimizing the microgrid. Mixed-integer linear programming (MILP) was the method implemented using commercial solvers without resorting to complex heuristics or decompositions techniques [100].

4.3.3. Energy management control

When multiple resources are available for generation and storage, optimization helps in deciding the operation strategies so that system performs most economically while reliably meeting customer demand. Proper management of resources can enhance the performance of HRES subsystems [101,102]. Zhao et al. [22] optimized reactive power output of wind farm and network structure simultaneously to minimize the system real power losses and the deviation of the bus voltage thereby achieving improved power control and voltage profile. Trifkovic et al. [31] described a power management scheme for a wind–PV–electrolyzer–FC integrated standalone system using decentralized adaptive model prediction control and decision making techniques. It was proved that running the electrolyzer below its rated power improved the efficiency of renewable energy generated and thereby a higher hydrogen generation. Díaz-González [19] proposed an energy management strategy for a flywheel-based energy storage device in a hierarchical manner to smooth the net power flow injected to the grid by a variable speed WT. The implemented techniques were vector control with a control algorithm. Reduction in costs and emissions has been attempted in many management strategies with optimization algorithms and methods. Abbaspour [103] proposed a two-objective optimization function (profit maximization and cost minimization) for power generation company with integrated wind and CAES. Without considering capital costs, it is found that the use of CAES results in 43% higher operational profits and 6.7% lower total load serving costs. Combination of optimization methods with AI techniques has also been attempted for improving energy management techniques. A generalized formulation for intelligent energy management of a microgrid was proposed by Chaouachi et al. [104] using artificial intelligence techniques jointly with linear-programming-based multi-objective optimization. The proposed multi-objective intelligent energy management aims to minimize the operation cost and the emission levels of a microgrid, taking into account its pre-operational variables as future availability of renewable energies and load demand. An energy management system based on an intelligent technique viz. distributed artificial intelligence with grey prediction has been adopted for an autonomous polygeneration microgrid in [105]. Garcı´a at al. [106] combined optimization with fuzzy logic control for energy management in an HRES system and showed improved performance. Managing uncertainties arising from renewable generation and load demand predictions are also considered as objectives for optimum operation of an HRES system. Mohammadi et al. [107] employed the Hong's Point estimate Method (PEM) to optimize a microgrid by modelling the uncertainty in the renewable power generation, the market prices and the load demands. Further investigation in Ref. [108] was done by applying an efficient stochastic framework by the use of probability density function of each uncertain variable and roulette wheel mechanism scenarios instead of the Hong's estimate. The stochastic framework captured approximately 3 times more uncertainties than the deterministic framework. The above stated works provide a different approach to energy management compared to conventional strategies based on just the SOC and power balances [109–111].

5. Optimization tools and techniques

To achieve the various objectives discussed in Section 4, many different tools and techniques have been developed and practiced, all aiming for a predefined "optimal design" criteria both offline and also in real time. Likewise, research has yielded a number of algorithms over time to determine the optimal operating conditions while functioning under predefined conditions. A brief overview of some of these tools and techniques is provided below.

5.1. Software tools for optimization

1. *HOMER (Hybrid Optimization Model for Electric Renewable):* was developed by NREL (National Renewable Energy Laboratory, USA). It has found immense usage in hybrid systems optimization all over the world. This software models the hybrid systems and performs optimization over a wide range of energy sources (or generators), converters and loads. The simulations can now be performed on data for both technical and economic factors. Data of nearly a year can be simulated in time-intervals of up to 1 min. Its salient features include its ability to investigate parameter changes and uncertainties un-intermittently. Versions of this software are available for researchers to download free of charge.
2. *GAMS (General Algebraic Modeling System):* is a modelling software which can simulate a large range of linear and non-linear optimization problems. The system is capable of handling complex situations due to its enhanced ability to adapt with the changes encountered. Many other tools have been formulated in GAMS modelling language such as *BALMOREL, MARKAL/TIMES, WILMAR Planning Tools* etc. Many projects have been realized using *BALMOREL* which is an open source free to download software model which can analyze electric and CHP systems for planning, market study, policy evaluations and security. *MARKAL/TIMES* and *WILMAR Planning Tools* are both commercially available tools with the first one being a research project of European Commission and later one a model developed by *ETSAP* by *IEA* [112,127–130].
3. *HYBRID2* was developed by the Renewable Energy Research Laboratory (RERL) of the University of Massachusetts. It is the software for modelling and simulating loads, sources and power conversion devices in an HRES. The simulation is very precise, as flexible time intervals can be defined. NREL suggests that the accuracy of HOMER optimized results can then be improved using *HYBRID2* [131]. This software is available for researchers free of charge.
4. *RETSCREEN* is the most downloaded tool of all simulation tools with more than 383,000 users spread across 222 countries. It is based on MS Excel. Technical and financial viability of renewable projects can be evaluated by comparing them with base case models of conventional systems.

Other softwares used in recent days are *INSEL*, *TRNSYS*, *RAPSIM (Remote Area Power Supply Simulator)*, *SOMES*, etc. [3,79]. Though

Table 3
Metahueristic optimization methods development timeline.

METHOD	DEVELOPER	YEAR
Evolutionary algorithm	John Holland at University of Michigan	Early 1970s
Simulated annealing	S. Kirkpatrick, C.D. Gellat and M.P. Vecchi	1983
Ant colony optimization	Marco Dorigo	1992
Genetic programming	John. R. Koza	1988
Particle swarm optimization	James Kennedy and Russel C. Earhart	1995
Harmony search algorithm	Zong Woo Geen	2001
Honey bee algorithm	S. Nakrani and C. Trovey	2004
Artificial bee colony algorithm	D. Karaboga	2005

Table 4
Account of optimization methods studied in literature survey.

Optimization category	Method of optimization	Optimization objectives	Year of publication
ACS	Ant colony algorithm	Achieving the minimum power loss and increment load balance factor of radial distribution networks with distributed generators [113]	Jul-10
EA	Differential evolutionary algorithm	Planned scheduling based on emission load dispatch and cost [55]	Feb-12
	Niching evolutionary algorithm (NEA).	Minimizing overall cost and emissions [56]	Jul-12
GA	Non-dominated sorting genetic algorithm (NSGA-II)	to increase reliability by reducing LPSP of the PV–WT–BESS system [114]	Apr-12
		minimize COE and emissions [65]	Jan-10
		Minimize power generation cost and to maximize life of lead–acid batteries [5]	Apr-13
	Genetic algorithm	Optimize the LCE [63]	Sep-11
		Minimizing cost of system for PV–WT system with LPSP as constraint [15]	May-08
	Genetic algorithm with linear program (GALP)	To determine the optimal capacity and operations of a VRB energy storage system [58]	Oct-11
	Chaotic quantum genetic algorithm	Ecomic dispatch problems for distribution [57]	Jul-12
HM	Modified ε-constraint method	To minimize total operation cost and emissions [64]	Jun-13
	Quasi-Newton algorithm	To decide the optimal combination for HRES while minimizing LCE [17]	Jul-07
	An original hardware-in-the loop (HIL) solution	Optimization of the frequency control mechanism of autonomous microgird with battery ESS [61]	May-12
PSO	Particle swarm optimization for designing	Optimal design of LC filter and its controlling parameters in Autonomous and Grid-Connected Modes [41]; to reduce costs in planning with ε-constraint method [42]	Mar-11; Jan-14
	Particle swarm optimization for sizing	To find optimal sites and corresponding sizes of renewable resources – to reduce the power loss in the radial distribution systems [45]; hybrid PSO with GSA for muti-distributed planning [90]	Jul-05; Apr-13
	Particle swarm optimization for control	To control flow of active and reactive power with power sharing b/w grid n utility highlighted under variable load conditions [52]	Feb-13
	Particle swarm optimization for regulation	Voltage and frequency regulation, steady state response, harmonic distortion analysis and power sharing are the main performance parameters optimized for grid-connected mode [51,31]	May-12 and June-13
	Particle swarm optimization and genetic algorithm	To find optimal sites and corresponding sizes of renewable resources – for autonomous operation [46]	Jan-14
	2 m Point Estimate Method (2m PEM) with self adaptive modification PSO method (SAM-θ-PSO)	To consider the uncertainties in cost minimization for renewable microgrids with storage devices [54]	Apr-13
	Hybrid PSO with Wavelet Mutation (HPSOWM) and Binary PSO (BPSO)	Minimize the system real power losses and the deviation of the bus voltage [22]	Jun-10
SA	Simulated annealing	To obtain optimal generator setting and battery charge–discharge schedules [115]	Mar-93
		Minimizing COE [83]	Jul-05
Software tool	Optimization using HOMER	9-different RES scenarios compared based on NPC of system [74]	Aug-11
		Four different compared based on minimum NPC [75]	Mar-12
	General algebraic modeling System (GAMS) software	A two-objective optimization function (profit maximization and cost minimization) for a integrated wind and CAES [63]	Oct-12
		To smooth the net power flow injected to the grid with a flywheel-based energy storage device [19]	May-13
		Minimization of the total thermal generation costs in islanded MG with ESS [57]	May-13
	HYBRID2	Reducing size of renewable DG by designing and simulating a HESS based HRES [116]	Aug-04

these tools can be extensively used to evaluate pre-feasibility, sizing, technical and economic studies, they still need to be made more flexible for increased usage in control, energy management and stability related studies. Even other tools are available now commercially which help in integrating CHP–thermal storage systems (*BALMOREL, GTMax, RAMSES*) and sometimes transport sector (*PERSEUS, STREAM,* and *WILMAR*) into renewable electric systems. Studies by Connolly et al. [112] and Sinha [3] give a very detailed comparison and discussion on the software tools available for analysing HRES. A few optimization studies carried out using some of these tools have been enlisted in Table 4.

5.2. Optimization algorithms for hybrid renewable energy system

Optimization of a problem refers to finding the maximum and minimum of a real function by computing the value of the function using inputs systematically selected from within an allowed set. Problems arising in many application areas of power systems are computationally hard to determine. For such problems, heuristic search techniques have been established since 1940s. Heuristics includes trial and error solution finding strategies for complex problems within real time limits. In an HRES, the real time problems are so complex that computing all the solutions is simply impossible. Also, sometimes the most efficient solution determined would be impossible to implement. Hence, the aim is to find efficiently good, but feasible solutions within time limits. The metaheuristic algorithms were developed in the 1980s and 90s. They include strategies that are nature-inspired as they have been developed based on the behaviour of nature. Table 3 gives a timeline of development of metaheuristic optimization methods. There are many types of metaheuristic algorithms. They can be either population-based or trajectory-based algorithms. Genetic algorithms can be listed as a population-based algorithm as it uses a population of strings, whereas hill-climbing algorithms are of trajectory-based style. The PSO involves memory characterised agents hence can be referred to as agent-based algorithms [117]. Erdinc [118] studied the optimum approaches for sizing of renewable energy systems. An insight into the functioning of some optimization algorithms which have been observed from the literature survey is presented in Table 4.

5.2.1. Differential evolution algorithm (DE)

It is a stochastic, population-based optimization algorithm. An objective function f can be expressed in a feasible region $X \subseteq R^D \rightarrow R$ for $X \neq \phi$. The aim is to find the minimum value that can be attained by f with constraints $x^* \in X$ such that

$$f(x^*) \leq f(x) \forall x \in X.\text{where } D\text{–number of real parameters.} \qquad (18)$$

The procedure for DE includes following steps:

- Initialization: The problem is initialized by selecting random parameters in predefined intervals $[x_j^L, x_j^U]$.

- Mutation: is employed to expand the search space. For every parameter vector $x_{i,G}$ initialized, mutants vectors $x_{r1,G}$, $x_{r2,G}$ and $x_{r3,G}$ are generated randomly. Where indices *i, r1, r2* and *r3* have to be distinct and *G* is the random generation number. A donor vector $v_{i,G+1}=x_{r1,G}+F(x_{r2,G} - x_{r3,G})$ is calculated with the mutant vectors.
- Recombination: The mutant solutions are then recombined with successful solutions in this step. A trial vector $u_{i,G+1}$ is obtained from $x_{i,G}$ and $v_{i,G+1}$ as

$$uj,i,G+1=\begin{cases} vj,i,G+1 & \text{if} \quad rand_{j,i}\le CR \quad \text{or} \quad j=I_{rand} \\ xj,i,G+1 & \text{if} \quad rand_{j,i}> CR \quad \text{or} \quad j\ne I_{rand} \end{cases} \tag{19}$$

where $i=1, 2,\ldots, N$; $j=1, 2,\ldots, D$ and I_{rand} is a random integer from [1, 2,…, *D*]
- Selection: Comparing the target vector $x_{i,G}$ and the trial vector $u_{i,G+1}$, the lowest of the two is selected for further iterations. Mutation, recombination and selection processes continue until some condition for stopping is reached. Recent studies use DE combined with more advanced methods and algorithms to achieved improved performance in hybrid microgrids [119,120].

5.2.2. Genetic algorithms (GA)

It is inspired by Darwin's theory of survival of fittest. An optimization function is encoded as arrays of bits or character strings to represent the chromosomes. These strings are then manipulated and tested for their fitness values to solve the problem concerned. GA consists of five processes. These are an initial random population generator, a "fitness" evaluation unit and genetic operators for "selection", "crossover" and "mutation" operations. The random population generator generates possible solutions which satisfy all constraints outlined in the problem definition. Next these solutions are evaluated based on their fitness values. "Selection" operator selects a predefined set of fit solutions. Using the "crossover" operator finds new solutions with the aim of producing hybrid individuals which have a higher fitness value as compared to their predecessors. A "Mutation" operator enables the algorithm to escape local minima entrapment problem. These steps are repeated until convergence is reached. GA was applied to sizing model for an HRES in 1997 by Hochmut [121]. Many variations of GA have evolved in the past. Chaotic quantum genetic algorithm is one such variation used by Liao [57]. It combines the GA and local search capability of quantum probability model with sensitivity of chaotic algorithms. Population initiation is done with a chaotic system using Logistic mapping and power output from generators is encoded using quantum bits and chromosomes. Then fitness evaluation is done to select best object followed by Quantum rotation to update. The process is repeated till convergence. Non-dominated sorting genetic algorithm (NSGA-II) was proposed by Deb in 2002 [122] and other scholars [5,65,114]. The entire parameter population is segregated into levels of non-dominance. Each parameter is assigned a fitness equal depending on the level. This algorithm has proven its ability to escape a local minimum effectively and is hence suitable for use in HRES sizing optimization problems. The disadvantage with GA is that its complexity increases with the number of parameters and thus coding difficulty also increases.

5.2.3. Particle swarm optimization (PSO)

It is an evolutionary agent-based technique which simulates the social behaviour of how a swarm moves in search of food together within a specific area. It is an iterative algorithm which finds the solution for a given objective function within a predefined space. It was developed in 1995 by James Kennedy (social-psychologist) and Russell Eberhart (electrical engineer) [123]. Here, each solution parameter is considered as a particle in the swarm with intelligence about its own and the common group behaviour. Each particle tracks two position values *pbest* and the *gbest* locations, which are the best solutions (fitness) that have been achieved so far by self and the group respectively. The basic concept of PSO is to accelerate toward the *pbest and gbest*, with an acceleration V_i^{k+1} which, is a weighted random integer calculated as follows. The velocity and position of particles are updated at the end of each iteration as follows:

$$V_i^{k+1}=wV_i^k+c_1rand_1(\ldots)x(pbesti-s_i^k)+c_2rand_2(\ldots)x(gbest-s_i^k)$$

$$s_i^{k+1}=s_i^k+V_i^{k+1} \tag{20}$$

Its simplicity is its advantage. Hence it is very easy to implement in any optimization software, thus making it the most sought after technique for HRES problems. It is also very fast. But if there are more than three components, it is more efficient to utilize GA approach. A multi-criteria approach was proposed to handle hybrid system (wind turbine generators, photovoltaic panels, and storage batteries) problems considering multiple design objectives including costs, reliability and emissions [39]. More than 20 varieties of PSO algorithms have been proposed since its advent. Hybrid Particle Swarm Optimization with Wavelet Mutation (HPSOWM) incorporates a GA's evolutionary operations of mutations with a dynamic mutating space by using a wavelet function [22]. HPSOWM performs more efficiently and achieves a faster convergence. The Binary Particle Swarm optimization (BPSO) algorithm was also introduced by Kennedy and Eberhart to enable using PSO for binary problems [22].

5.2.4. Simulated annealing (SA)

is a random search technique which replicates the annealing process of metals. A metal is melted at high temperatures and then cooled and frozen into a crystalline state with the minimum energy. As a result, the metal develops larger crystal sizes with reduced defects in its metallic structure. The control of temperature is most significant in the whole process. The application of simulated annealing was first introduced to optimization problems by Kirkpatrick, Gelatt and Vecchi in 1983. The process involves perturbing a random current state to a new state at fixed temperature *T*. Let ΔE be the difference in energy between current and new state and if $\Delta E<0$ (new state is lower), then the new state is accepted as current state else if $\Delta E\ge 0$, a new state is accepted with probability

$$Pr(accepted)=\exp(-DE/k_BT). \tag{21}$$

Eventually, thermal equilibrium is achieved by the system at temperature *T*. At reaching equilibrium the process can be repeated by lowering the temperature. Same algorithm can be used for combinational optimization problems where energy *E* now corresponds to the cost function *C* and temperature *T* corresponds to control parameter *c*.

$$Pr\{configuration=i\}=1/Q(c)\exp(-C(i)/c). \tag{22}$$

SA in hybrid system sizing is less popular as compared to GA or PSO. Fung et al. [115] applied SA to a diesel generator, a sine wave inverter and a controller unit to obtain optimal generator setting and battery charge–discharge schedules for a given daily load cycle. Katsigiannis et al. [83] compared SA to another metaheuristic method called tabu-search algorithm for a sizing problem in an HRES with the objective of minimizing COE. Results concluded that SA was faster to converge but less efficient than the other method.

5.2.5. Ant colony algorithm (ACS)

Marco Dorigo pioneered the research in this area in 1992. Research on behaviour of ants has pointed the presence of a specific pheromone which is used by ants to mark the path for other ants. As more and more ants follow the same path more pheromone is deposited on the path. On the contrary if a path is not utilized then the smell of the pheromone deposited there will vanish away. Hence ants are always attracted to paths with stronger pheromone smells which usually lead to places rich in food. In this way, the ants mark the best (shortest) path towards food. ACS simulates this behaviour to find the most optimal solution for a given objective function. First all ants are placed at a starting state from where they build paths to an end state with repetitive application of state transition rule as follows [113]:

$$P_{ij}^{k} = \begin{cases} \frac{[\tau ij]^{\alpha}[\eta ij]^{\beta}}{\sum_{u \in Jk(i)} [\tau iu]^{\alpha}[\eta iu]^{\beta}} & \text{if} \quad j \in Jk(i) \\ 0 \quad \text{otherwise} \end{cases} \tag{23}$$

$$j = \begin{cases} \arg\max u \in Jk(i)\{[\tau iu]^{\alpha}[\eta iu]^{\beta}\} & \text{if } q \le q0 \\ S \quad \text{otherwise} \end{cases} \tag{24}$$

where τ is the pheromone on a path between node i and j; α and β are control parameters; η is the inverse of the edge distance; $Jk(i)$ is the set of nodes ant k positioned on node i has to visit; q is a random number uniformly distributed in [0 1]; q_0 is a parameter $(0 \le q_0 \le 1)$. Depending on the distribution given in (23) a random variable S selected. Also the pheromone on the path on which an ant travels is modified which is given by the following updating equation:

$$\tau ij = (1-\rho)\tau ij \tag{25}$$

where ρ is a heuristically defined parameter. Once all ants have reached the end state pheromones on path are again updated as follows to direct the ants in the next iteration

$$\tau ij = (1-\sigma)\tau ij + \sigma\Delta\tau ij \tag{26}$$

where

$$\Delta\tau ij = \begin{cases} \frac{Q}{Lbest}, & \text{if route } (i,j) \text{ is a global best path} \\ 0, \quad \text{otherwise} \end{cases} \tag{27}$$

where $\Delta\tau ij$ is the distance of the globally best tour from the beginning of the trial and σ is the pheromone decay parameter. This makes the search more directed. The ACS algorithm has been proposed to reduce distribution system losses and increment load balance factor of radial distribution networks and proved to be better than the GA by achieving 44.626% of average loss reduction [113].

Many more approaches have been developed to efficiently and economically solve problems for hybrid energy systems. Among them are tabu search [83], honey bee mating algorithm, multi-criteria decision analysis optimization [124], bacterial foraging algorithm, biogeography based optimization (BBO) [125], artificial immune system algorithm, and firefly algorithms. Future research may pave the way for hybridization and multi-objective implementation of bio-inspired solutions. Attempts to exploit advantages and disadvantages of different algorithms have been made by implementing hybrid algorithms [84–87,126]. These approaches have been proved to be more fast, accurate and powerful than individual systems. The choice of algorithm to be implemented depends solely on the application and hence a thorough understanding is needed to justify its merits and demerits. High dimensional problems like sizing algorithms perform better with PSO than GA. Artificial intelligent techniques are also applied with optimization algorithms in some power system applications [106].

6. Conclusion

This review paper has briefed on Hybrid Renewable Energy Systems (HRES), the system metrics utilized for developing optimization objectives and software tools/algorithms employed to optimize the system. Solar and wind energy conversion systems are widely being integrated into hybrid systems as they efficiently complement each other. A brief study on this system and their modelling has been included. Current weakest link, of all energy systems, is the energy storage. With accelerated research and development, the efficiency and lifetime of storage systems have been improved to ensure optimal utilization. Of all the ESS described above, redox batteries and sodium–sulphur batteries are found to be very promising in HRES for a continuous supply of energy. Flywheels can provide deeper discharges whereas lithium batteries are also matching up with reduced cost and easy availability. It is necessary to mention that different storage systems offer different benefits and hence the selection of an appropriate system has to be done judiciously depending on the requirements. The system metrics which act as the core for optimizing the system have been enlisted. These metrics mainly entail the technical and economic performance of a system. Also, environmental factors can be included in these metrics, like the avoided cost of emissions and avoided costs of capacity etc. Optimization methods are finding many applications in development and implementation of HRES. An account of a diverse range of optimization objectives that have been targeted in power system applications has been included with a clear framework. Though economic and environmental objectives are most widely considered, power quality and stability constraints are also necessary for integration of HRES generated power with the utility grid. Hence, they may be included in future research works for improved analysis and implementation. Finally, a summary of the optimization tools and metaheuristic techniques – their application and analysis has been presented. Many tools had been developed which help in optimizing the hybrid systems integrating renewables. Some of these are offered as open source to be downloaded and the rest are being developed commercially and tailored for serving a predetermined problem. The system requirements and specifications judged based on system metrics discussed above are the governing factors for the appropriate selection of optimization tool/technique to be used. Further research will help in improving the power quality from HRES and to overcome the shortfalls of current scenario.

References

[1] Mitra I, Degner T, Braun M. Distributed generation and microgrids for small island electrification in developing countries: a review. Sol Energy Soc India 2008;18(1):6–20.
[2] Lasseter RH. Microgrids and distributed generation. J. Energy Eng. 2007;133 (3):144–9.
[3] Sinha S, Chandel SS. Review of software tools for hybrid renewable energy systems. Renew Sustain Energy Rev 2014;32:192–205.
[4] Zhou A, Qu B-Y, Li H, Zhao S-H, Suganthan PN, Zhang Q. Multiobjective evolutionary algorithms: a survey of the state of the art. Swarm Evolutionary Comput 2011;1(1):32–49.
[5] Zhao B, Zhang X, Chen J, Wang C. Operation optimization of standalone microgrids considering lifetime characteristics of battery energy storage system. IEEE Trans Sustain Energy 2013;4(4):934–43.
[6] Deshmukh MK, Deshmukh SS. Modeling of hybrid renewable energy systems. Renew Sustain Energy Rev 2008;12:235–49.
[7] Serrano E, Rus G, García-Martínez J. Nanotechnology for sustainable energy. Renew Sustain Energy Rev 2009;13(9):2373–84.
[8] Zäch M, Hägglund C, Chakarov D, Kasemo B. Nanoscience and nanotechnology for advanced energy systems. Curr Opin Solid State Mater Sci 2006;10(3–4):132–43.
[9] Guo KW. Green nanotechnology of trends in future energy: a review. Int J Energy Res 2012;36(1):1–17.
[10] Banosa R, Manzano-Agugliarob F, Montoyab FG, Gila C, Alcaydeb A, Gómezc J. Optimization methods applied to renewable and sustainable energy—a review. Renew Sustain Energy Rev 2011;15:1753–66.
[11] 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.

[12] Hongxing Y, Lu L, Zhou W. A novel optimization sizing model for hybrid solar-wind power generation system. Sol Energy 2007;81:76–84.
[13] Bajpai P, Dash V. Hybrid renewable energy systems for power generation in stand-alone applications: a review. Renew Sustain Energy Rev 2012;16: 2926–39.
[14] Luna-Rubio R, Trejo-Perea M, Vargas-Vazquez D, Rıos-Moreno GJ. Optimal sizing of renewable hybrids energy systems: a review of methodologies. Sol Energy 2012;86:1077–88.
[15] Hongxing Y, Zhou W, Chengzhi L. Optimal design and techno-economic analysis of a hybrid solar–wind power generation system. Appl Energy 2009;86:163–9.
[16] Hongxing Y, Lu L, Zhou W. A novel optimization sizing model for hybrid solar-wind power generation system. Sol Energy 2007;81:76–84.
[17] Ashok S. Optimised model for community-based hybrid energy system. Renew Energy 2007;32:1155–64.
[18] Qi Z, Lin E. Integrated power control for small wind power system. J Power Sources 2012;217:322–8.
[19] Díaz-González F, Sumper A, Gomis-Bellmunt O, Bianchi FD. Energy management of flywheel-based energy storage device for wind power smoothing. Appl Energy 2013;110:207–19.
[20] Elma O, Selamogullari US. A comparative sizing analysis of a renewable energy supplied stand-alone house considering both demand side and source side dynamics. Appl Energy 2012;96:400–8.
[21] Sarrias R, Fernández LM, García CA, Jurado F. Coordinate operation of power sources in a doubly-fed induction generator wind turbine/battery hybrid power system. J Power Sources 2012;205:354–66.
[22] Zhao J, Li X, Hao J, Lua J. Reactive power control of a wind farm made up with doubly fed induction generators in distribution system. Electr Power Syst Res 2010;80(6):698–706.
[23] Kwasinski A, Krishnamurthy V, Song J, Sharma R. Availability evaluation of micro-grids for resistant power supply during natural disasters. IEEE Trans. Smart Grid 2012;3(4):2007–18.
[24] Tana X, Wanga H. Advances and trends of energy storage technology in microgrid. Electr Power Energy Syst 2013;44:179–91.
[25] Ghofrani M, Arabali A, Amoli ME, Fadali MS. Energy storage application for performance enhancement of wind integration. IEEE Trans Power Syst 2013;28(4):4803–11.
[26] Koohi-Kamali S, Tyagi VV, Rahim NA, Panwar NL, Mokhlis H. Emergence of energy storage technologies as the solution for reliable operation of smart power systems: a review. Renew Sustain Energy Rev 2013;25:135–65.
[27] Díaz-González F, Sumper A, Gomis-Bellmunt O, Villafáfila-Robles R. A review of energy storage technologies for wind power applications. Renew Sustain Energy Rev 2012;16(4):2154–71.
[28] Ingram E. Balancing the grid with pumped storage. Renewableenergyworld. com; 2010.
[29] Nyserda. Final report: compressed air energy storage engineering and economic study; 2009.
[30] Banham-Hall DD, Taylor GA, Smith CA, Irving MR. Flow batteries for enhancingwind power integration. IEEE Trans Power Syst 2012;27(3): 1690–7.
[31] Trifkovic M, Sheikhzadeh M, Nigim K, Daoutidis P. Modeling and control of a renewable hybrid energy system with hydrogen storage. IEEE Trans Control Syst Technol 2014;22(1):169–79.
[32] Liu H, Jiang J. Flywheel energy storage—an upswing technology for energy sustainability. Energy Build 2007;39(5):599–604.
[33] Tixador P. Super conducting magnetic energy storage: status and perspective; 2008. IEEE/CSC & ESAS european superconductivity news forum 2008;3.
[34] Hadjipaschalis I, Poullikkas A, Efthimiou V. Overview of current and future energy storage technologies for electric power applications. Renew Sustain Energy Rev 2009;13:1513–22.
[35] Xiao X, Yi H, Kang Q, Nie J. A two-level energy storage system for wind energy systems. Proc Environ Sci 2012;12:130–6.
[36] Whittingham MS. History, evolution, and future status of energy storage. Proc IEEE 2012;13:1518–34.
[37] Wies RW, Johnson RA, Agrawal AN, Chubb TJ. Simulink model for economic analysis and environmental impacts of a PV with diesel–battery system for remote villages. IEEE Trans Power Syst 2005;20(2):692–700.
[38] Poonpun P, Jewell WT. Analysis of the cost per kilowatt hour to store electricity. IEEE Trans Energy Convers 2008;23(2):529–34.
[39] Wang L, Singh C. Multicriteria design of hybrid power generation systems based on a modified particle swarm optimization algorithm. IEEE Trans Energy Convers 2009;24(1):163–72.
[40] Bilal BO, Sambou V, Ndiaye PA, Kébé CMF, Ndongo M. Multi-objective design of PV–wind–batteries hybrid systems by minimizing the annualized cost system and the loss of power supply probability. IEEE Int Conf Ind Technol (ICIT) 2013;1:861–8.
[41] Maheri A. Multi-objective design optimisation of standalone hybrid wind–PV diesel systems under uncertainties. Renew Energy 2014;66:650–61.
[42] Sharafi M, ELMekkawy TY. Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach. Renew Energy 2014;68:67–79.
[43] Hassan MA, Abido MA. Optimal design of microgrids in autonomous and grid-connected modes using particle swarm optimization. IEEE Trans Power Electron 2011;26(3):755–69.
[44] Arefifar SA, YA-RI Mohamed, EL-Fouly THM. Optimum microgrid design for enhancing reliability and supply-security. IEEE Trans Smart Grid 2013;4 (3):1567–75.
[45] Bhumkittipich K, Phuangpornpitak W. Optimal placement and sizing of distributed generation for power loss reduction using particle swarm optimization. Energy Proc 2013;34:307–17.
[46] Kirthiga V, Daniel SA, Gurunathan S. A methodology for transforming an existing distribution network into sustainable micro-grid. IEEE Trans Sustain Energy 2013;4(1):31–41.
[47] Afzalan E, Taghikhani MA, Sedighizadeh M. Optimal placement and sizing of distributed generators in radial distribution networks using shuffled frog leaping algorithm. Int J Energy Eng 2012;2(3):73–7.
[48] Dagdougui H, Minciardi R, Ouammi A, Robba M, Sacile R. A dynamic decision model for the real-time control of hybrid renewable energy production systems. IEEE Syst J 2010;4(3):1932–8184.
[49] Huayllas TEDC, Ramos DS, Vasquez-Arnez RL. Microgrid Systems: current status and challenges. IEEE/PES Transm Distrib Conf Expos 2010;1:7–12.
[50] Dasgupta S, Mohan SN, Sahoo SK, Panda SK. A plug and play operational approach for implementation of and autonomous-micro-grid system. IEEE Trans Ind Inform 2012;8(3):615–29.
[51] Al-Saedi W, Lachowicz SW, Habibi D, Bass O. Power quality enhancement in autonomous microgrid operation using particle swarm optimization. Electr Power Energy Syst 2012;42:139–49.
[52] Al-Saedi W, Lachowicz SW, Habibi D, Bass O. Power flow control in grid-connected microgrid operation using particle swarm optimization under variable load conditions. Electr Power Energy Syst 2013;49:76–85.
[53] Al-Saedi W, Lachowicz SW, Habibi D, Bass O. Voltage and frequency regulation based DG unit in an autonomous microgrid operation using particle swarm optimization. Electr Power Energy Syst 2013;53:742–51.
[54] Baziar A, Kavousi-Fard A. Considering uncertainty in the optimal energy management of renewable MG including storage devices. Renew Energy 2013;59:158–66.
[55] Basu AK, Bhattacharya A, Chaudhry S, Chowdhry SP. Planned scheduling for economic power sharing CHP based microgrid. IEEE Transa Power Syst 2012;27(1):30–8.
[56] Conti S, Nicolosi R, Rizzo SA, Zeineldin H. Optimal dispatching of distributed generators and storage systems for MV islanded microgrids. IEEE Trans Power Deliv 2010;27(3):1243–51.
[57] Liao GC. Solve environmental economic dispatch of smart microgrid containing distributed generation system—Using chaotic quantum genetic algorithm. Int J Electr Power Energy Syst 2012;43(1):779–87.
[58] Leou R. An economic analysis model for the energy storage systems applied to a distribution substation. Electr Power Energy Syst 2012;34:132–7.
[59] Etxeberria A, Vechiu I, Camblong H, Vinassa JM. Comparison of three topologies and controls of a hybrid energy storage system for microgrids. Energy Convers Manag 2012;54:113–21.
[60] Chedid R, Rahman S. Unit sizing and control of hybrid wind-solar power systems. IEEE Trans Energy Convers 1997;12(1):79–85.
[61] Serban I, Teodorescu R, Marinescu C. Analysis and optimization of the battery energy storage systems for frequency control in autonomous microgrids. In: Proccedings of the 3rd IEEE international symposium on power electronics for distributed generation systems; 2012.
[62] Sigrist L, Lobato E, Rouco L. Energy storage systems providing primary reserve and peak shaving in small isolated power systems: an economic assessment. Int J Electr Power Energy Syst 2013;53:675–83.
[63] Vrettos EI, Papathanassiou SA. Operating policy and optimal sizing of a high penetration RES–BESS system for small isolated grids. IEEE Trans Energy Convers 2011;26(3):744–56.
[64] Aghaei J, Alizadeh MI. Multi-objective self-scheduling of CHP based microgrids considering demand response programs and ESSS. Energy 2013;55 (15):1044–54.
[65] Katsigiannis YA, Georgilakis PS, Karapidakis ES. Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables. Renew Power Gen 2010;4(5):404–19.
[66] Sundararagavan S, Baker E. Evaluating energy storage technologies for wind power integration. Sol Energy 2012;86:2707–17.
[67] Tewari S, Mohan N. Value of NaS energy storage toward integrating wind: results from the wind to battery project. IEEE Trans Power Syst 2013;28 (1):532–41.
[68] Khalid M, Savkin AV. Minimization and control of battery energy storage for wind power smoothing: aggregated distributed and semi-distributed storage. Renew Energy 2014;64:105–12.
[69] Brekken TKA, Yokochi A, von Jouanne A, Yen ZZ, Hapke HM, Halamay DA. Optimal energy storage sizing and control for wind power applications. IEEE Trans Sustain Energy 2011;2(1):69–77.
[70] Giannakoudis G, Papadopoulos AI, Seferlis P, Voutetakis S. Optimum design and operation under uncertainty of power systems using renewable energy sources and hydrogen storage. Int J Hydrog Energy 2009;35(3):872–91.
[71] Vosen SR, Keller JO. Hybrid energy storage systems for stand-alone electric power systems: optimization of system performance and cost through control strategies. Int J Hydrog Energy 1999;24:1139–56.
[72] Choi ME, Kim SW, Seo SW. Energy management optimization in a battery/supercapacitor hybrid energy storage system. IEEE Trans Smart Grid 2012;3 (1):463–72.

[73] Thounthong P, Luksanasakul A, Koseeyaporn P, Davat B. Intelligent model-based control of a standalone photovoltaic/fuel cell power plant with supercapacitor energy storage. IEEE Trans Sustain Energy 2013;4(1):240–9.
[74] Prodromidis GN, Coutelieris FA. Simulations of economical and technical feasibility of battery and flywheel hybrid energy storage systems in autonomous projects. Renew Energy 2011;39:149–53.
[75] Hafez O, Bhattacharya K. Optimal planning and design of a renewable energy based supply system for microgrids. Renew Energy 2012;45:7–15.
[76] Raya H, Moubayed N. Economic study on batteries and caes for a lebanese hybrid wind/diesel system. In: Proceedings of the international conference on technological advances in electrical, electronics and computer engineering, vol. 1; 2013. p. 329–33.
[77] Kahrobaee S, Asgarpoor S. Optimum planning and operation of compressed air energy storage with wind energy integration. In: Proceedings of the North American power symposium, vol. 1; 2013. p. 1–6.
[78] 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(4).
[79] Bernal-Agustı´n JL, Dufo-Lo´pez R. Simulation and optimization of stand-alone hybrid renewable energy systems. Renew Sustain Energy Rev 2009;13:2111–8.
[80] Ekren O, Ekren BY. Size optimization of a PV/wind hybrid energy conversion system with battery storage using response surface methodology. Appl Energy 2008;85:1086–101.
[81] Ekren O, Ekren BY, Ozerdem B. Break-even analysis and size optimization of a PV/wind hybrid energy conversion system with battery storage – a case study. Appl Energy 2008;86:1043–54.
[82] 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.
[83] 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(3):330–8.
[84] Abbes D, Martinez A, Champenois G. Life cycle cost, embodied energy and loss of power supplyprobability for the optimal design of hybrid power systems. Math Comput Simul 2014;98:46–62.
[85] Di-Silvestre ML, Graditi G, Sanseverino ER. A generalized framework for optimal sizing of distributed energy resources in micro-grids using an indicator-based swarm approach. IEEE Trans Ind Inform 2014;10(1):152–62.
[86] 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: 412–425.
[87] Arnette A, Zobel CW. An optimization model for regional renewable energy development. Renew Sustain Energy Rev 2012;16:4606–15.
[88] Zhang X, Tan SC, Li G, Li J, Feng Z. Components sizing of hybrid energy systems via the optimization of power dispatch simulations. Energy 2013;52:165–72.
[89] Perera ATD, Attalage RA, K. Perera, Dassanayake VPC. Designing standalone hybrid energy systems minimizing initial investment, life cycle cost and pollutant emission. Energy 2013;54:220–30.
[90] Tan WS, Hassan MY, Rahman HA, Abdullah MP, Hussin F. Multi-distributed generation planning using hybrid particle swarm optimisation- gravitational search algorithm including voltage rise issue. IET Gen Transm Distrib 2013;7 (9):929–42.
[91] Imran MA, Kowsalya M. Optimal size and siting of multiple distributed generators in distribution system using bacterial foraging optimization in distribution system using bacterial foraging optimization. Swarm Evolut Comput 2013;15:58–65.
[92] Suvire GO, Mercado PE. DSTATCOM with flywheel energy storage system for wind energy applications: Control design and simulation. Electr Power Syst Res 2009;80:345–53.
[93] Farhoodnea M, Mohamed A, Shareef H, Zayandehroodi H. Optimum placement of active power conditioners by a dynamic discrete firefly algorithm to mitigate the negative power quality effects of renewable energy-based generators. Int J Electr Power Energy Syst 2014;61:305–17.
[94] Younsi S, Jraidi M, Hamrouni N, Cherif A. Modelling and control of hybrid renewable energy system connected to AC grid. Int J Comput Sci Eng 2011;3 (12):3854–65.
[95] Arabali A, Ghofrani M, Amoli ME, Fadali MS, Baghzouz Y. Genetic-algorithm-based optimization approach for energy management. IEEE Trans Power Deliv 2013;28(1):162–70.
[96] Zhang D, Li S, Zeng P, Zang C. Optimal microgrid control and power-flow study with different bidding policies by using powerworld simulator. IEEE Trans Sustain Energy 2014;5(1):282–92.
[97] Vahidinasab V. Optimal distributed energy resources planning in a competitive electricity market: multiobjective optimization and probabilistic design. Renew Energy 2014;66:354–63.
[98] Zhang Y, Gatsis N, Giannakis GB. Robust energy management for microgrids with high-penetration renewables. IEEE Trans Sustain Energy 2013;4 (4):944–53.
[99] Maa X, Wang Y, Qin J. Generic model of a community-based microgrid integrating wind turbines, photovoltaics and CHP generations. Appl Energy 2013;112:1475–82.
[100] Parisio A, Rikos E, Glielmo L. A model predictive control approach to microgrid operation optimization. IEEE Trans Control Syst Technol 2014;22 (5):1813–27. http://dx.doi.org/10.1109/TCST.2013.2295737.
[101] Carapellucci R, Giordano L. Modeling and optimization of an energy generation island based on renewable technologies and hydrogen storage systems. Int J Hydrog Energy 2012;37:2081–93.
[102] Pourmousavi SA, Nehrir MH, Colson CM, Wang C. Real-time energy management of a stand-alone hybrid wind-microturbine energy system using particle swarm optimization. IEEE Trans Sustain Energy 2010;1(3):193–201.
[103] Abbaspour M, Satkin M, Ivatloo BM, Lotfi FH, Noorollahi Y. Optimal operation scheduling of wind power integrated with compressed air energy storage. Renew Energy 2013;51:53–9.
[104] Chaouachi A, Kamel RM, Andoulsi R, Nagasaka K. Multiobjective intelligent energy management for a microgrid. IEEE Trans Ind Electron 2013;60 (4):1688–99.
[105] Kyriakarakos G, Piromalis DD, Dounis AL, Arvanitis KG, Papadakis G. Intelligent demand side energy management system for autonomous polygeneration microgrids. Appl Energy 2013;103:39–51.
[106] Garcı´a P, Torreglosa JP, Ferna´ndez LM, Jurado F. Optimal energy management system for standalone wind turbine/photovoltaic/hydrogen/battery hybrid system with supervisory control based on fuzzy logic. Int J Hydrog Energy 2013;38:14146–58.
[107] Mohammadi S, Mozafari B, Solimani S, Niknam T. An adaptive modified firefly optimisation algorithm based on hong's point estimate method to optimal operation management in a microgrid with consideration of uncertainties. Energy 2013;51:339–48.
[108] Mohammadi S, Soleymani S, Mozafari B. Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices. Electr Power Energy Syst 2013;54:525–35.
[109] Zhoua K, Ferreirab JA. Haanb SWHD. Optimal energy management strategy and system sizing method for stand-alone photovoltaic-hydrogen systems. Int J Hydrog Energy 2008;33(2):477–89.
[110] Ipsakis D, Voutetakis S, Seferlis P, Stergiopoulos F, Elmasides C. Power management strategies for a stand-alone power system using renewable energy sources and hydrogen storage. Int J Hydrog Energy 2009;34:7081–95.
[111] Dursun E, Kilic O. Comparative evaluation of different power management strategies of a stand-alone PV/wind/PEMFC hybrid power system. Int J Electr Power Energy Syst 2012;34(1):81–9.
[112] 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.
[113] Wu Y, Lee C, Liu L, Tsai S. Study of reconfiguration for the distribution system with distributed generators. IEEE Trans Power Deliv 2010;25(3):1678–85.
[114] Abbes D, Martinez1 A, Champenois G. Eco-design optimisation of an autonomous hybrid wind–photovoltaic system with battery storage. IET Renew Power Gen 2012;6(5):358–71.
[115] Fung CC, Hoand SCY, Nayar CV. Optimisation of a hybrid energy system using Simulated Annealing technique. IEEE TENCON 1993;5:235–8.
[116] Mills A, Al-Hallaj S. Simulation of hydrogen-based hybrid systems using hybrid2. Int J Hydrog Energy 2004;29(10):991–9.
[117] Yang XS. Engineering optimization—an introduction with metaheuristic applications. Hoboken, New Jersey: John Wiley and sons, Inc.; 2010.
[118] Erdinc O, Uzunoglu M. Optimum design of hybrid renewable energy systems overview of different approaches. Renew Sustain Energy Rev 2012;16:1412–25.
[119] Li Y, Wang Y, Li B. A hybrid artificial bee colony assisted differential evolution algorithm for optimal reactive power flow. Electr Power Energy Syst 2013;52:25–33.
[120] Hemmati M, Amjady N, Ehsan M. System modeling and optimization for islanded micro-grid using multi-cross learning-based chaotic differential evolution algorithm. Int J Electr Power Energy Syst 2014;56:349–60.
[121] Hochmut GCS. A combined optimisation concept for the design and operation strategy of hybrid-PV energy systems. Sol Energy 1997;61(2):77–87.
[122] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evolut Comput 2002;6(2):182–97.
[123] Kennedy J, Eberhart R. Particle swarm optimization. IEEE Int Conf Proc Neural Netw 1995;4:1942–8.
[124] Alsayed M, Cacciato M, Scarcella G, Scelba G. Multicriteria optimal sizing of photovoltaic-wind turbine grid connected systems. IEEE Trans Energy Convers 2013;28(2):370–9.
[125] Bansal AK, Kumar R, Gupta RA. Economic analysis and power management of a small autonomous hybrid power system using biogeography based optimization algorithm. IEEE Trans Smart Grid 2013;4(1):638–48.
[126] Zheng YJ, Chen SY, Lin Y, Wang WL. Bio-inspired optimization of sustainable energy systems: a review. Math Probl Eng: Hindawi Publishing Corporation; 2013. article ID-354523.
[127] Upadhyay S, Sharma MP. A review on configurations, controland sizing methodologies of hybrid energy systems. Renew Sustain Energy Rev 2014;38:47–63.
[128] 〈http://www.balmorel.com/〉.
[129] 〈http://www.iea-etsap.org/Energy_Technologies/Energy_Technology.asp〉.
[130] 〈http://www.wilmar.risoe.dk/〉.
[131] 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.