Optimizing Hybrid Renewable Energy Systems: A Review

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Abstract

With the fast progression of renewable energy markets, the importance of combining different sources of power into a hybrid renewable energy system (HRES) has gained more attraction. These hybrid systems can overcome limitations of the individual generating technologies in terms of their fuel efficiency, economics, reliability and flexibility. One of the main concerns is the stochastic nature of photovoltaic (PV) and wind energy resources. Wind is often not correlated with load patterns and may be discarded sometimes when abundantly available. Also, solar energy is only available during the day time. A hybrid energy system consisting of energy storage, renewable and nonrenewable generation can alleviate the issues associated with renewable uncertainties and fluctuations. Large number of random variables and parameters in a hybrid energy system requires an optimization that most efficiently sizes the hybrid system components to realize the economic, technical and designing objectives. This chapter provides an overview of optimal sizing and optimization algorithms for hybrid renewable energy systems as well as different objective functions considered for designing such systems.

Keywords: hybrid energy system, objectives, optimization, renewable energy, sizing

1. Introduction

Use of solar and wind power has become more and more significant, attractive and less expensive, since the oil crises in the early 1970s. Even though there is a need to use renewable energy sources, the main problem with it is the dependency on environmental conditions like solar irradiance and wind speed. The individual energy sources cannot provide continuous power supply to the load because of the uncertainty and on-and-off nature of the environmental conditions [1]. Combining intermittent renewable energy sources with other dispatchable sources of energy such as biogas and fuel cells as well as energy storage systems provides a solution to address this challenge. Hybrid renewable energy system (HRES) is

a term to describe the combination of two or more renewable and nonrenewable energy sources. Basic components of such systems are power sources (wind turbine, diesel engine generator and solar arrays), the battery and the power management center, which regulates power production from each of the sources [1]. As an example of such systems, microgrid is an integrated energy system that includes energy resources, loads and storages. Microgrids found popularity over the years due to the needs for distributed generation and with the integration of HRESs including photovoltaic (PV) and wind generators as well as the battery storage devices. The microgrids have many benefits for both utility grids and customers, such as higher power quality, reduction in carbon emission, energy efficiency and reduced costs. Another capability of microgrids is islanding which allows the microgrid to be disconnected from the utility grid in the case of upstream disturbances or voltage fluctuations [2].

Operating an HRES requires optimizing its performance while satisfying its physical and technical constraints. Therefore, optimization tools, techniques and applications have found popularity to achieve these goals [3].

This chapter provides an overview of the optimization techniques, optimization objectives and component sizing for hybrid renewable energy systems. Section 2 summarizes optimal sizing results of hybrid renewable energy systems in different studies. Section 3 describes the three commonly used algorithms to optimize the operation and modelling of hybrid energy systems: classical algorithms, metaheuristic algorithms and hybrid algorithms. Section 4 reviews different objective functions, constraints and indexes in use for the hybrid system optimization.

2. Optimal sizing for hybrid renewable energy systems

HRESs require an optimal design for their component sizing to economically, efficiently and reliably meet the objectives outlined in Section 4. **Table 1** provides examples of studies related

References	Components of the hybrid system	Load specifications	Sizing results
[4]	Wind turbine (WT), photovoltaic (PV) and battery	225 kW peak, 25 kW base	195 kW WT, 85 kW PV, 230 kW microturbine, 2.14 kAh battery
[5]	WT, PV, microturbine and battery	1.5 kW constant	6 kW WT, 12.8 kW PV, 6 kAh battery
[6]	WT, PV, diesel and battery	26 kW peak, 5 kW base	15 kW WT, 24 kW PV50 kW diesel, 151 kWh battery
[7]	WT, PV and battery	1500 W	78 × 100 W PV, 2 × 6 kW WT, 5000 Ah (24 V) battery
[8]	PV, diesel and battery	3.5 kW peak, 0.25 kW base	2.8 kW DG, 4.2 m^2 PV, 2.75 kWh battery
[9]	Wind, PV and energy storage	1 MW peak, 0.4 MW base	2.096 MW wind, 0 MW PV, 6.576 MWh energy storage
[10]	Wind, PV and energy storage		2.42 MW wind, 0 MW PV, 6.7878 MWh energy storage

Table 1. Optimal sizing of HRESs.

to HRES optimal sizing along with details regarding the hybrid system components, their load characteristics and sizing results.

3. Optimization algorithms for hybrid renewable energy systems

Optimization algorithms are ways of computing maximum or minimum of mathematical functions. Different objectives can be considered when optimizing a system's design. Maximizing the efficiency of the system and minimizing the cost of its production are examples of such objectives. Optimization methods and techniques can help to solve complex problems. When designing a HRES, we have to consider its components' performances. The main goal is to have a better performance with reduced costs. These goals can be achieved through optimal modelling of the system [11]. The three commonly used modelling and optimization techniques for hybrid systems are classical algorithms, metaheuristic methods and hybrid of two or more optimization techniques.

3.1. Classical techniques

Classical optimization algorithms use differential calculus to find optimum solutions for differentiable and continuous functions. The classical methods have limited capabilities for applications whose objective functions are not differentiable and/or continuous. Several conventional optimization methods have been used for hybrid energy systems. Linear programming model (LPM), dynamic programming (DP) and nonlinear programming (NLP) are examples of classical algorithms widely in use for optimizing HRESs.

Linear programming model (LPM) studies the cases in which the objective function is linear and the design variable space is specified using only linear equalities and inequalities.

This model has been used in several studies for HRES optimization [12–17]. These studies take advantage of the LPM capabilities to stochastically perform reliability and economic analysis. However, the energy delivery capability of the overall system is adversely affected by failure of any of the renewables to function properly [11].

Nonlinear programming (NLP) model studies the general cases in which the objective functions or the constraints or both contain nonlinear parts. This model has been used in some studies [18, 19]. The model enables solving complex problems with simple operations. However, high number of iterations for numerical methods such as NLP increases the computational burden of the problem [11].

Dynamic programming (DP) studies the cases in which the optimization strategy is based on splitting the problem into smaller subproblems. This method helps solving sequential or multistage problems in which the stages are related together. One advantage of DP is the ability of optimizing each stage. Therefore, it can address the complexity of larger systems. However, high number of recursive functions for DP makes the coding and implementation complex and confusing [11]. Ref. [20] provides an example of studies that uses DP for HRES optimization.

3.2. Metaheuristic techniques

Metaheuristic search techniques have been extensively used for optimizing complex systems such as HRESs due to their capabilities to give efficient, accurate and optimal solutions. These algorithms are nature-inspired as their developments are based on behaviour of nature. Examples of metaheuristic optimization in use for HRESs include genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA) and ant colony (AC) algorithm.

Genetic algorithm (GA) is an evolutionary population-based algorithm that includes several operations such as initialization, mutation, crossover and selection to ensure finding an optimal solution to a given problem. Several studies used GA to optimize the design and operation of HRESs [21–28]. GA may result in local optima if it is not initialized or designed properly.

Particle swarm optimization (PSO) simulates the social behaviour of how a swarm moves to find food in a specific area. It is an iterative algorithm with the goal of finding a solution for a given objective function within a given space. Its application for optimizing HRESs has been investigated in several studies [29–34]. PSO is efficient in solving the scattering and optimization problems. However, it requires several modifications due to its complex and conflicted nature [11].

Simulated annealing (SA) is based on the metal annealing processing. A metal gets melted at a very high temperature and then it gets cooled down and finally gets frozen into a crystalline state with the minimum amount of energy. As a result, the metal develops larger crystal sizes with a minimum amount of defects in its metallic structure. SA has been used for hybrid system sizing in several studies such as [35].

Ant colony (AC) algorithm is based on behaviour of ants to use a specific pheromone to mark the path for other ants. More pheromones are left on the path as more ants follow the same path. On the other hand, if a path is not used, then the smell of the last pheromone will disappear. Ants are more attracted to the paths with the most pheromone smells and it usually leads them to places with most foods. By following this method, ants mark the shortest path towards food. AC simulates this behaviour to find the most optimal solution for a given objective function [36]. This algorithm has been used for size optimization for hybrid systems [37]. AC algorithms have high convergence speed but require long-term memory space [11].

3.3. Hybrid techniques

Combination of two or more optimization techniques can overcome limitations of the individual techniques mentioned above to provide more effective and reliable solutions for HRESs. This combination is referred to as hybrid techniques. Examples of such techniques are SA-Tabu search; Monte Carlo simulation (MCS)-PSO; hybrid iterative/GA; MODO (multiobjective design optimization)/GA; artificial neural fuzzy interface system (ANFIS); artificial neural network/GA/MCS; PSO/DE (differential evolution); evolutionary

algorithms and simulation optimization-MCS which have been used in several studies for optimizing HRESs [38–47]. Although hybrid techniques enhance the overall performance of the optimization, they may suffer from some limitations. Examples of such limitations are the partial optimism of the hybrid MCS-PSO method in [40], suboptimal solutions of the hybrid iterative/GA in [41], cost-sizing compromise of the hybrid methods in [42, 43], design complexity of the hybrid ANN/GA/MCS method in [44], random adjusting of the inertia weight of the evolutionary algorithm in [46] and coding complexity of the optimization-MCS in [47].

4. Optimization objectives for HRESs

Various criteria are considered for optimal design and component sizing of HRESs. These criteria can be broadly categorized as economic and technical. Economic criteria are used to minimize costs of HRESs. Technical criteria include reliability, efficiency and environmental objectives to supply the load demand of HRESs at desired reliability levels with maximum efficiency and minimum greenhouse gas emissions.

4.1. Cost optimization

HRESs often times include higher capital costs and lower operation and maintenance (O&M) costs which require an optimization to determine the compromise solution between the costs and benefits. Cost optimization of hybrid renewable energy systems includes minimizing energy cost, net present cost (NPC) and any other costs associated with such systems.

4.1.1. Energy cost minimization

Several studies have investigated minimizing levelized cost of energy (LCE) for HRESs. LCE is the ratio of total cost of the hybrid system to the annual energy supplied by the system. **Table 2** summarizes the related research works, their objective functions, techniques in use for optimization and their main findings.

4.1.2. Net present cost minimization

Net present cost (NPC) of an HRES is defined as the total present value of the system that includes the initial cost of the system components as well as the replacement and maintenance cost within the project lifetime. The objective here is to minimize the NPC of HRESs. **Table 3** summarizes the related research works, their objective functions, techniques in use for optimization and their main findings.

4.1.3. Other cost-related optimization

Other cost-related optimizations include minimizing life cycle cost (LCC), levelized unit electricity cost (LUEC), annualized cost of the system (ACS), capital cost (CC) of the hybrid

References	Objective function(s)	Optimization technique	Findings
[33]	$$\min LCE = \frac{\left(\left[\dfrac{d(1+d)^n}{(1+d)^n - 1} \times ICC\right]\right) + \left(ANN + [O\,\&M \times n]\right)}{8760 \times CF_{net}}$$ d = interest rate (%); n = operational life (years); ICC: installed capital cost ($/kW); ANN = the annualized costs (insurance, other expenses); $O\&M$ = operation and maintenance cost ($/kW); CF_{net} = net capacity factor; 8760 = hours per year.	PSO	Levelized cost of energy is achieved which is based on several factors such as financing, insurance, maintenance and other depreciation factors.
[48]	$$\min LCE = \sum_{i=1}^{n}\left(\frac{CO_i}{y_i}\right) \bigg/ E_{an} = \frac{\dfrac{CO_{PV}}{Y_{PV}} + \dfrac{CO_W}{Y_W} + CO_{Bat}\,/\,Y_{Bat}}{E_{an}(\gamma,\beta,h)}$$ CO_{PV} = the sum of capital cost and maintenance cost in the lifespan of the whole PV system; CO_W = the sum of capital cost and replacement or maintenance cost in the lifespan of the whole wind power generation system; CO_{Bat} = the sum of capital cost and the lifespan maintenance cost of battery bank; Y_{PV} = the lifetime year of PV system; Y_W = the lifetime year of wind system; Y_{Bat} = the lifetime year of battery bank; $E_{an}(\gamma,\beta,h)$ = the annual energy supplied from the hybrid solar-wind system.		An optimal model is developed to ensure capacity sizes are ideal for different hybrid system components including PV system, wind system and battery bank.
[49]	$$\min CE = \left[\frac{r(1+r)^n}{r(1+r)^n - 1}\right]\left[\frac{P}{87.6k}\right] + [O\,\&M]$$ CE = cost of energy in U.S. cents/kWh; k = annual capacity factor in per-unit; n = amortization period, years; $O\&M$ = operation and maintenance cost in U.S. cents/kWh; P = installed (capital) cost in U.S. $/kW; r = fixed annual interest rate in per-unit.		An optimal sizing model is designed for solar wind systems to meet energy demands.
[50, 51]	$$\min LCE = \frac{TAC}{E_{tot}} = \frac{PVC \times \left[\dfrac{d(1+d)^n}{(1+d)^n - 1}\right]}{E_{tot}}$$ PVC = present value of costs; TAC = total annualized cost; E_{tot} = the annual total energy; d = discount rate; n = useful lifetime.		Monthly and daily energy balances are evaluated for optimal configurations of hybrid PV/wind systems.

References	Objective function(s)	Optimization technique	Findings
[52]	$$\min LCE = \frac{C_{acap}\left(x\right)+C_{amain}\left(x\right)+C_{arep}}{E_{annual}}$$ E_{annual} = the annual consumed energy (kWh/year); C_{arep} = levelized replacement cost of energy; C_{acap} = levelized capital cost of energy; $C_{amain}(x)$ = levelized maintenance and operation cost of energy.	GA	A compromise solution is obtained between the levelized cost of energy and CO_2 emission.
[53]	$$\min LCE = \frac{\left(C + L + \sum_{n=1}^{N}\frac{\left(OM+1\right)\times C}{\left(1+r\right)^{n}}\right)}{\left(\sum_{n=1}^{N}\frac{S \times TF \times \eta \times \left(1-d\right)^{n}}{\left(1+r\right)^{n}}\right)}$$ S = solar resource; TF = tracking factor; d = annual degradation rate; η = performance factor; OM = maintenance cost; C = cost of the system; L = cost of the required land; r = discount rate.		Levelized cost of energy is estimated on the basis of electricity pricing for the entire life cycle of a given hybrid system.
[54]	$$\min LCE = \frac{TLCC \times CRF}{E}.\frac{d\left(1+d\right)^{n}}{\left(1+d\right)^{n}-1}$$ $TLCC$ = total life-cycle cost; CRF = capital recovery factor; n = year; E = the annual generated energy (kWh); d = annual degradation rate.		A hybrid wind-PV system is designed for an off-grid electrification project considering several parameters such as number, type and location of generators, controllers, batteries and inverters.
[55]	$$\min LCE = \frac{NPC}{\left\{\sum_{n=1}^{N}\left[\frac{Q_{n}}{\left(1+d\right)^{n}}\right]\right\}}$$ Q_{n} = energy in year n (kWh); d = annual discount rate; NPC = net present cost ($).	GA	PV-diesel hybrid systems are shown to be optimal economic solutions to incorporate renewable energy into pumping for drip irrigation facilities.

Table 2. Optimization of HRESs for minimizing LCE.

system, total cost of the system (TCS) and average generation cost (AGC). **Table 4** summarizes the related research works, their objective functions, techniques in use for optimization and their main findings.

4.2. Technical optimization

Besides the cost optimization explained in Section 4.1, technical objectives can be also optimized when designing an HRES. Technical objectives include, but are not limited to,

References	Objective function	Optimization technique	Findings
[56]	$$COE = \frac{TNPC \times CRF}{\sum_{t=1}^{8760} E_{Gen(t)}}$$ $$CRF(d,n) = \frac{di(1+di)^n}{(1+di)^n}$$ COE = cost of energy (%); $TNPC$ = total net present cost; CRF = capital recovery factor; $E_{Gen(t)}$ = total generated electricity over a period; di = discount rate (%); d = day of the year (d); n = life of the plant (year).	PSO	A hybrid system of solar, diesel, hydro, biomass and biogas energy is optimally designed to meet the load demand of seven villages in India. CO_2 emissions, renewable fraction, net present cost and cost of energy are included in the model.
[57]	$$\min NPC = \frac{TAC}{CRF(i,N)}$$ TAC = the total annualized cost ($/year); CRF = the capital recovery factor; i = annual real interest rate; N = the project lifetime in years.		The PV/diesel/battery HRES configuration is found as the optimum solution among different hybrid system configurations for different study areas within the geopolitical zones of Nigeria.
[58]	$$\min NPC = \frac{(ACC + ARC + AMC)}{\left[\frac{i(1+i)^j}{(1+i)^j - 1} \right]}$$ ACC = the annualized capital cost; ARC = the annualized replacement cost; AMC = the annualized maintenance cost; j = the project lifetime; i = the annual real interest rate.	ANN/GA	A model is developed to evaluate technical and economic impacts of charge controller operation and coulombic efficiency on stand-alone hybrid PV/wind/diesel/battery power systems.
[59]	$$\min NPC = \sum_{N=1}^{N=t} f_{d,N} \left(C_{cap} + C_{rep} + C_{main} - C_s \right)$$ t = the project life time C_{cap}, C_{rep}, C_{main} and C_s = the nominal capital, the replacement, the O&M cost and the salvage costs, respectively.		Two scenarios are modeled for stand-alone hybrid renewable systems with hydrogen production and storage. The hybrid wind/PV model was found to provide the optimal configuration for the study area.

Table 3. Optimization of HRESs for minimizing NPC.

satisfying desired reliability levels based on loss of power supply probability (LPSP) or loss of load probability (LOL) [64–66], minimizing cost/efficiency ratio [67], minimizing carbon emissions [68] and maximizing power availability [69]. **Table 5** summarizes the related research works, their objective functions, techniques in use for optimization and their main findings.

References	Objective function	Optimization technique	Findings
[42]	$\min LCC = \dfrac{PW}{Pr} + C_{inst} + C_{maint} x \times x \times \dfrac{1-x^n}{1-x} + PW_{replace}$ LCC = life cycle cost; Pr = present worth factor for an item that will be purchased n years later; PW = power; C_{inst} = installation cost; C_{maint} = maintenance cost; $PW_{replace}$ = present worth of the component considering that it needs to be replaced periodically.	Multiobjective programming (MOP)/GA	A multiobjective optimization is developed to combine life cycle cost, embodied energy and loss of power supply probability as the objectives for designing an autonomous hybrid wind/PV/ battery system. An optimal economic and environmental design is obtained among the Pareto solutions based on the designer's preferences.
[60]	$\min LUEC\left(\dfrac{\$}{kWh}\right) = \dfrac{LCC \times CRF}{\sum_{t=1}^{8760} E_{Gen}(t)}$ $LUEC$ = levelized unit electricity cost; $E_{Gen}(t)$ = total generated electricity over a period; CRF = capital recovery factor; LCC = the life cycle cost of the hybrid system.		An optimization is developed to incorporate reliability and cost models for a grid-independent hybrid PV/ wind system.
[61]	$\min CC = \alpha.N_{PV} + \beta.N_{batt} + C_0$ CC = capital cost of the hybrid system; α = cost of a PV module; β = cost of a battery; N_{PV} = number of PV modules; N_{batt} = number of battery storage; C_0 = the total constant costs including the cost of design, installation and a wind turbine.	GA	Optimal component sizes are calculated for a standalone hybrid wind-PV-battery system.
[7]	$\min ACS = C_{cap}.\left[\dfrac{i(1+i)^{Y_{proj}}}{(1+i)^{Y_{proj}}-1}\right]$ $(PV + Wind + Bat + Tower)$ $+ C_{rep}\left[\dfrac{i}{(1+i)^{Y_{rep}}-1}\right](Bat)$ $+ C_{amain}(PV + Wind + Bat + Tower)$ ACS = annualized cost of the system; C_{cap} = the initial capital cost of each component; Y_{proj} = the component lifetime, year; C_{amain} = annualized maintenance cost; Y_{rep} = the component (battery) lifetime, year; C_{rep} = replacement cost of the component (battery); i = annual interest rate.	GA	Optimal PV module number and slope angle, wind turbine number and installation height and battery capacity are calculated to design a hybrid system for a telecommunication relay station.
[62]	$\min TCS = \sum_{i=w,S,b} (I_i - S_{P_i} + OM_{P_i})$ w, s, b = the wind power, solar power and battery storage, respectively; I_i, S_{pi}, OM_{pi} = the initial cost, present worth of salvage value and present worth of operation and maintenance (OM) cost for equipment i.	PSO	Total cost of a stand-alone hybrid power generation system is reduced while maximizing its reliability.

References	Objective function	Optimization technique	Findings
[63]	$$\min C_{av} = \frac{\left\{\dfrac{r(1+r)^n}{(1+r)^n - 1} + m\right\} \sum_i P_i R_i}{(87.6)\sum_i R_i K_i}$$ C_{av} = the average generation cost; i = the summation index to include all devices; K_i = the load factor for ith device; m = the operation and maintenance charge rate in per unit; n = the amortization period in years; P_i = the capital cost for the ith device; R_i = the rating in kW of the ith device.		An integrated renewable energy optimization model (IREOM) is developed to size renewable energy systems for desired reliability levels.

Table 4. Optimization of HRESs for minimizing other costs.

References	Objective function	Optimization technique	Findings
[64]	$$LPSP = \frac{\sum_{t=0}^{T} Power.failure.time\left(P_{supplied}(t) < P_{needed}(t)\right)}{N}$$ N = the number of time intervals; t = time, h; T = temperature, K; $P_{supplied}$ = power supplied from the hybrid system; P_{needed} = power needed.	GA	Optimal sizing of HRES is achieved for a custom required loss of power supply probability.
[65]	$$LOLP = \frac{\sum_{i=1}^{n} hours\left(I_{supplied}(t) < I_{needed}(t)\right)}{n}$$ $LOLP$ = loss of load probability; $I_{needed}(t)$ = the current required for the load at hour t; $I_{supplied}(t)$ = the current supplied by HRES at hour t; n = number of samples.		Lower levels of LOLP result in higher costs of the hybrid system and vice versa.
[66]	$$LSPS = \Pr\left\{E_{b,t} \le E_{B\,min}, for\,t \le T\right\}$$ $E_{b,t}$ = energy stored in the batteries in hour t; E_{Bmin} = battery minimum allowable energy level.	GA	The total capital cost is minimized while satisfying the constraint of the loss of power supply probability (LPSP).
[67]	$$\sum_{j=1}^{6}\sum_{i=1}^{1}\left(\frac{C_{ij}}{\eta_{ij}}\right)x_{ij}$$ C = unit cost of the system; η = efficiency of the system; i = renewable energy system; j = end use; x = quantum of renewable energy.	Multiobjective programming (MOP)	Analysis was done to find out the reliability factor of solar PV power plant and wind turbine generator.
[68]	$$C_{co_2} = CP_{co_2}(E_i \times R_{i,co_2})$$ C_{co_2} = the gravimetric cost penalty for carbon emissions; CP_{co_2} = monetary cost of co_2; E_i = the annual system component power consumption/ utilization (kWhr); R_{i,co_2} = specific co_2 emission rate.	PSO	A multiobjective optimization is developed to meet the load and water desalination demand of an HRES.

References	Objective function	Optimization technique	Findings
[69]	$A = 1 - \dfrac{DNM}{D}$ $$DNM = \sum_{t=1}^{T} P_{Batt_{MIN}}(t) - P_{Batt_{SOC}}(t) - (P_{PV}(t) + P_{wind}(t) + P_{Grid}(t) - P_{D}(t)) \times u(t)$$ DNM = demand not met (kWh/year); A = index of availability; D = yearly demand; $P_{Batt_{MIN}}(t)$ = minimum allowable storage level at time t; $P_{Batt_{SOC}}(t)$ = state of charge of battery bank at time t; $P_{Grid}(t)$ = power purchased from utility at time t; $P_{wind}(t)$ = wind power at time t; $P_{D}(t)$ = demand at time t; $P_{PV}(t)$ = photovoltaic power at time t; T = operational duration under consideration; $U(t)$ = the step function which is zero if the supply power is greater than or equal to demand and one if the demand is not met.	Multiobjective genetic algorithm (MOGA)	A multiobjective optimization is developed that considers the availability of the generated electricity and cost of the equipment for the system design.

Table 5. Optimization of HRESs for technical objectives.

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