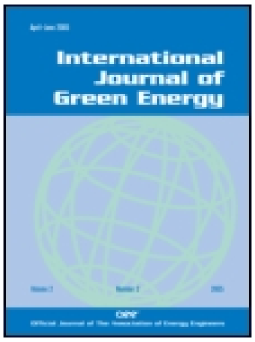

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Optimal Design Methods for Hybrid Renewable Energy Systems

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Renewable and hybrid energy systems (HESs) are expanding due to environmental concerns of climate change, air pollution, and depleting fossil fuels. Moreover, HESs can be cost effective in comparison with conventional power plants. This article reviews current methods for designing optimal HESs. The survey shows these systems are often developed on a medium scale in remote areas and stand-alone, but there is a global growing interest for larger scale deployments that are grid connected. Examples of HESs are PV–wind–battery and PV–diesel–battery. PV and wind energy sources are the most widely adopted. Diesel and batteries are often used but hydrogen is increasing as a clean energy carrier. The design of an efficient HES is challenging because HES models are nonlinear, non-convex, and composed of mixed-type variables that cannot be solved by traditional optimization methods. Alternatively, two types of approaches are typically used for designing optimal HESs: simulation-based optimization and metaheuristic optimization methods. Simulation-based optimization methods are limited in view of human intervention that makes them tedious, time consuming, and error prone. Metaheuristics are more efficient because they can handle automatically a range of complexities. In particular, multi-objective optimization (MOO) metaheuristics are the most appropriate for optimal HES because HES models involve multiple objectives at the same time such as cost, performance, supply/demand management, grid limitations, and so forth. This article shows that the energy research community has not fully utilized state-of-the-art MOO metaheuristics. More recent MOO metaheuristics could be used such as robust optimization and interactive optimization.

Keywords: Hybrid energy systems, Renewable energy, Optimization, Simulation, Multi-objective optimization, Metaheuristics

Introduction

Renewable energy systems are in expansion around the world because of the environmental concerns due to global warming, new carbon pricing regulations arising out of these concerns, and nuclear safety concerns especially after the Fukushima nuclear accident. For example, Germany declared that it plans to shut down their nuclear plants by 2022. In addition, the supply of fossil fuels is decreasing while the demand for energy is rapidly increasing. Consequently, energy systems such as photovoltaic (PV), wind, and fuel cells (FCs) are attractive alternatives because they are profuse, clean, and decentralized. A challenge with solar and wind resources is that they are intermittent and not constantly available. The combination of multiple renewable energy sources (RESs) is a sustainable solution for developing *constant* hybrid stand-alone energy systems, and also more reliable and lower cost systems (Muselli, Notton, and Louche 1999; Bagen 2005).

Several renewable energy projects have proven to be efficient and economically viable on a smaller scale, especially in remote areas such as: islands (Koroneos, Michailidis, and Moussiopoulos 2004; Ashraf et al. 2008) or desert areas (Ghoneim 2006). Usually, these energy systems are not fully implemented from RESs. Challenges include the high cost of the RES plants and storage (Kyung and Soung 1998; Bernal-Agustín and Dufo-López 2009a,b). However, the RES-based systems are still being expanded faster than expected; by 2020, it is expected to have over 30% of world energy supply originating from pure RESs (Bilgena et al. 2008). As the RES market grows, the prices of the components will decrease as a consequence of higher demand and technological advancements. Currently, RESs are still often combined with other conventional energy systems to form hybrid energy systems (HESs) such as PV–diesel–battery or PV–wind–battery (Bernal-Agustín and Dufo-López 2009a,b).

Designing *optimal* HESs is a complex task because of the difficulty of accurately predicting the output of these HESs. This optimization complexity arises for several reasons. First, there are a high number of variables involved in the energy design optimization problem. Second, there are conflicting objectives that make the optimization problem complex such as cost, performance, supply/demand management, grid limitations, and so forth. Also, coupled nonlinearities, non-convexities, and mixed-type variables often eliminate the possibility of using conventional optimization methods to solve such problems. This article reviews the simulation and optimization techniques applied to RES-based systems with a particular focus on RESs.

Renewable Energy Systems Modelings

This section describes some of the existing models for commonly used RES, such as PV, wind, and FCs.

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Modeling of Photovoltaic Systems

Understanding factors that affect the performance of PV modules is of great importance in order to achieve a precise anticipation of the PV module performance under variable climatic conditions. Many researchers worked in this direction. Overstraeten and Mertens (1986) developed the fundamental model of PV cells. Borowy and Salameh (1996) introduced a simplified model that calculates the maximum power output for a PV module based on the solar radiation and the ambient temperature. Jones and Underwood (2002) proposed a more complete model by calculating the PV power output efficiency model. Kerr and Cuevas (2003) introduced a model for calculating current–voltage (*I*–*V*) of PV modules by measuring pen-circuit voltage under variable light intensity. Nishioka et al. (2003) studied the temperature impact on the PV system annual output; it appears that the annual energy output of the PV system increases by about 1% for every 0.1%/°C temperature coefficient improvement. Stamenic, Smiley, and Karim (2004) examined low irradiance efficiency of PV modules installed on buildings. Zhou, Yang, and Fang (2007) introduced a "simple" simulation model for PV array performance predictions under operating conditions, with limited data available from PV module manufacturers. Mondol et al. (2005) developed a simulator for building integrated PV; the monthly average error between measured and predicted PV output was estimated to be 6.79%.

Modeling of Wind Systems

The modeling of wind energy systems includes wind turbine specifications and generator modeling. One of the simplest models to simulate the power output of a wind turbine was proposed by Ghali, Abd El Aziz, and Syam (1997); they used a probabilistic approach to simulate a hybrid PV–wind–battery energy system. Borowy and Salameh (1994, 1996) used a statistical method for calculating the power output from a wind turbine; they assumed the wind speed distribution to be a Weibull distribution. Karaki, Chedid, and Ramadan (1999) proposed a probabilistic model to simulate an autonomous wind energy conversion system composed of several turbines connected to a battery. Lu, Yang, and Burnett (2002) and Nehrir et al. (2000) developed an algorithm that simulates the power output from the wind turbine based on wind average speed, the electrical load, and the power curve. The wind turbine power curves do not always represent wind turbine power output with exactitude because they neglect instantaneous wind speed variations, and therefore, undermine the wind turbine performance (Muljadi and Butterfield 2001). Therefore, Zamani and Riahy (2008) introduced a new way for calculating the wind turbine output power by taking into consideration the wind speed variations.

Modeling of Hydrogen Fuel Cells

The hydrogen fits well hybrid RESs because of several reasons (Naterer et al. 2008). It is decentralized and intermittent supply in similar fashion as the wind and PV RESs. Also, It can become economically more viable and the predominant steam-methane reforming technology if merged properly with other RESs. In addition, the hydrogen can be reused as backup power generator, for regenerating electricity during peak hours, or used as is for transportation or other purposes.

Once the hydrogen is generated, it can be reconverted to electricity using FC technology. An FC is an electrochemical mechanism to generate electrical current (DC) from hydrogen and oxygen. Initially, Vanhanen et al. (1994) proposed a simulation PV–hydrogen system that generates hydrogen for PV panels, and then it reconverts it back to electricity. Then Amphlett et al. (1994), Kim et al. (1995), and Lee, Lalk, and Appleby (1998) worked on modeling of proton exchange membrane FC stack. Mann et al. (2000) and Fowler et al. (2002) continued to work on more precise models such as the degradation effect on the FC performance. Later, Cheddie and Munroe (2005) presented a review on proton exchange membrane FC modeling. In this review, they categorize the FC models as analytical, semi-empirical, and mechanistic. More recently, Mann et al. (2006, 2007) emphasized on activation and concentration polarization.

Another aspect regarding hydrogen that needs to be addressed is its storage. The hydrogen storage is even more critical in HES because solar and wind energy sources are inconsistent. Deshmukh and Boehm (2008) categorize current available hydrogen storage technologies as compressed hydrogen, liquid hydrogen, metal hydrides, and carbon-based materials (fullerenes, carbon nanotubes, activated carbons). An extensive literature review of PV, wind, and FC models can be found in Bañosa et al. (2011).

Simulation-Based Optimization of Energy System Components

Currently, researchers working on RESs are mainly focusing on solar and wind energy sources. The PV array area, the specificities of wind turbines, and the storage capacity have an important role in operation of hybrid PV–wind energy systems, while satisfying load (Wu and Liu 1996). The most common renewable stand-alone HESs are: PV–wind–battery, PV–diesel–battery, and hydroelectric–PV–wind–battery. None of these are *completely benign* renewable energy systems because of the battery component. The solar and wind systems are intermittent sources of energy, which require storage like a battery to form a PV–wind–battery system (Bernal-Agustín and Dufo-López 2009a,b), or a backup energy source such as diesel to form PV–wind–diesel systems (Bernal-Agustín and Dufo-López 2009b). In both cases, the HES is not completely renewable. The most common RES-based systems are not completely sufficient by themselves because of the intermittence of the wind and solar sources. Hydrogen is a cleaner alternative for energy storage, and it can be used for regenerating electricity by using FCs.

The HES designs are mainly dependent on the performance of their respective components. In order to forecast the system's performance, these components should be modeled and simulated. Then their combination could be evaluated to determine if it satisfies the demand load. If the power output estimation from these individual components is accurate enough, their combination can deliver power at the lowest cost.

Most of the simulation papers for HESs use the HOMER (Hybrid Optimization Model for Electric Renewables) tool (HOMER 2010), developed by NREL (National Renewable

Energy Laboratory, USA) because of its capabilities and flexibility. It can optimize a wide range of energy components: PV generator, batteries, wind turbines, hydraulic turbines, AC generators, FCs, electrolyzers, hydrogen tanks, AC–DC bidirectional converters, and boilers. The loads can be different types: AC, DC, and/or hydrogen or thermal loads. In addition, the tool is available free of charge.

Simulation-Based Optimization of Photovoltaic Systems

Shaahid and Elhadidy (2007) used the HOMER tool for cost optimization of a PV–diesel–battery system to supply a shopping center in a desert area. The HES reduced the diesel consumption and pollution by 27%. Shaahid and El-Amin (2009) used HOMER for finding an optimal design of a PV–diesel–battery HES, rather than diesel-only, for supplying a remote village in Saudi Arabia. The study examined the effect of PV/battery penetration on the cost of electricity, the unmet load, the electricity excess generation, percentage of fuel savings, and reduction in carbon emissions. The results showed that the optimal combination is the PV–diesel–battery rather than diesel-only or PV–diesel. The percentage of fuel savings by using a hybrid PV–diesel–battery energy system (2.5 MW PV, 4.5 MW diesel system, 1 h storage, 27% PV penetration) is 27% less than using diesel-only. In addition, the carbon emissions decrease by 24% (1005 tons/year) as compared to the diesel-only scenario. Li et al. (2008) used simulation methods for the development of a stand-alone PV system. Due to the intermittent nature of the solar energy, they considered batteries and/or FCs for energy storage. The hybrid PV–battery–FC energy system appeared to be the cheapest, most efficient, and least demanding in terms of PV module numbers as compared to either single storage system.

Wies et al. (2005) simulated, with Simulink and HOMER, a real hybrid PV–diesel–battery energy system located in Alaska. They compared it with a system with only a diesel generator, and another diesel–battery system to supply energy for the same load. The results indicated that the system with only a diesel generator had a lower installation cost, but higher operation and maintenance costs.

Simulation-Based Optimization of Wind Systems

Himri et al. (2008) used the HOMER software tool for the optimization of energy production, life cycle cost, and the greenhouse gas emissions of an HES. The hybrid wind–diesel energy system is a grid-connected power plant supplying energy to a remote village. The results show that the wind–diesel hybrid system becomes feasible when the wind speed reaches 5.48 m/s and the fuel price is 0.162$/L or more. The maximum annual capacity shortage did not impact in any way on the system optimization. Lu, Yang, and Burnett (2002) used probabilistic models to select the optimal (maximum power output) turbine characteristics, depending on the yearly wind properties. They found that hub height is an important factor. At 37 m, the wind turbine can function for 6820 h (77.85%) a year and generate 32,400 KWh with a capacity factor of 0.387 for Waglan island.

Simulation-Based Optimization of Fuel-Cell Systems

The hydrogen FCs fit well with HESs for several reasons (Naterer et al. 2008). First, FCs provide a decentralized supply in a similar fashion to wind and solar RESs. Second, hydrogen can be generated during off-peak periods where electricity prices are low. Third, the hydrogen FC can be reused as a backup power source; it can be used, for example, for regenerating electricity during peak hours. The FC mechanism generates direct current (DC) from hydrogen and oxygen.

As mentioned previously, Li et al. (2008) examined on a combination of FCs with PV–battery systems. Deshmukh and Boehm investigated variant forms of hydrogen storage technologies that are currently available (Deshmukh and Boehm 2008): compressed hydrogen, liquid hydrogen, metal hydrides, and carbon-based materials (fluorescence, carbon nanotubes, activated carbons).

Simulation-Based Optimization of PV–Wind Systems

McGowan and Manwell (1999) discussed PV–wind–diesel–batteries HESs in different locations in the world using the HYBRID2 tool (Hybrid2 2010). They concluded that hybrid energy-related research should further examine the reliability of components and systems, improve the documentation and monitoring of system performance, and reduce the cost of the renewable energy components. Furthermore, they designed PV–wind–diesel–battery systems for different applications in South America (McGowan et al. 1996). They found by comparing HYBRID2 and SOMES tools that they provide similar results, and they can be used to design and size such systems. However, there is no universal tool yet, and different types of problems need to be solved through the use of different approaches and tools. Karaki, Chedid, and Ramadan (1999) examine simulation algorithms for PV–wind–battery systems. They report on economics of hybrid PV–wind–battery energy systems. However, the battery capacity is limited, depending on the required charging/discharging cycle time. Elhadidy and Shaahid (2000) and Elhadidy (2002) studied the performance of possible variances of PV–wind–diesel systems. It has been found that PV panels are economically not yet viable for desert areas in Saudi Arabia. Nfah, Ngundam, and Tchinda (2007) proposed a design for a PV–wind–diesel–battery system located in a remote area in the north of Cameroon. They demonstrated that the HES can generate 70–2585 kWh/year rather than extending the grid.

Diaf et al. (2008) studied the optimization of economic and technical performance of a stand-alone hybrid PV–wind–battery energy system on Corsica island. They compared the optimum dimensions of the system in five sites on the island. The results showed the HES offers a better performance than a single source system. The PV system was not affected by changing sites; however, the wind system dropped from 40% power generation to 20%, depending on site location.

Dalton, Lockington, and Baldock (2008) worked on the design optimization of a stand-alone renewable energy PV–wind–battery–diesel system, using HOMER and HYBRIDS tools, for a large hotel (4100 beds) located in a subtropical coastal area in Australia. More specifically, they compared diesel generator-only, PV–wind–battery, and PV–wind–battery–diesel hybrid technologies. Three objectives were considered: the net present cost (NPC), renewable fraction (RF), and payback time. The result showed that it is possible to build a completely RES that meets the demand load. However, a hybrid diesel–wind–battery configuration provides the lowest NPC result with a resultant RF of 76%. The NPC is reduced by 50%, and the greenhouse gas emissions by 65%.

Mondal and Denich (2010) studied the potential of PV, wind, biomass, and hydro energy sources in Bangladesh. The results showed that PV grid-connected sources have the highest potential for the country. Prodromidis and Coutelieris (2010) examined an existing RES installed in Leicestershire, UK. The system is a stand-alone PV–wind–FC. By using the HOMER tool, it was determined how to optimize the use of the system and the cost impact of connecting the RES system to the grid. Results showed that in the long term, the connection to the grid will be costly.

Balamurugan, Ashok, and Jose (2009) used the HOMER tool for designing an HES composed of biomass–PV–wind–battery in a remote area. The objective was a combined maximization of the supply of energy to the loads and minimization of the supply of energy from the sources. A sensitivity analysis was performed for the load, wind speed, and solar radiation. The proposed system satisfied the load demand, nonlinear seasonal variations, and equipment constraints of three different typical villages in India.

Figure 1 is an example of a hybrid PV–wind modeling taken from Zhou et al. (2010).

Simulation-Based Optimization of Solar–Wind–Fuel-Cell Systems

Dufo-López, Bernal-Agustín, and Mendoza (2009) worked first (case A) on the design and economic analysis of hybrid PV–wind energy systems. In addition (case B), they considered the use of these systems for generating hydrogen when the amount of electricity is not needed by the demand load. Finally (case C), the reuse of hydrogen was considered for regenerating back electricity when the demand is high. The results (case A) showed that hybrid PV–wind energy systems match well and they are more economical than the use of a unique energy source. For case B, the generation of hydrogen for selling purposes appeared to be economically viable only for locations having a high average wind speed (>4.66 m/s). For case C, the use of hydrogen for regenerating electricity by FCs was not economically viable based on the electricity prices in Spain. The authors attribute this to a low energetic efficiency rate of the electricity-hydrogen-electricity process. However, if the electricity prices were higher or the energetic efficiency rate improved, the model would become viable.

Zervas et al. (2007) developed a framework for HES that used hydrogen for energy storage. Thus, they tested the framework with a PV–FC system connected to a grid in Greece. The proposed tool is especially useful for HESs that incorporate hydrogen systems.

Figure 2 is an example of a PV–FC (hydrogen) model taken from Hwang et al. (2009).

Optimization of Energy System Components

Several papers have been published regarding the optimization of hybrid energy sources. However, this study focuses on recent studies published in the last decade. Usually, an optimum combination of hybrid energy sources needs to address several objectives. Among them, the system and the production costs should be minimal, the load demand should be met, and the power should be reliable. Sometimes, HES is optimized by taking all the objectives at the same time. And sometimes, one objective is optimized whereas other objectives are transformed into constraints. Both approaches are described in the next subsections.

Mono Objective Optimization for Hybrid Energy System Design

Koutroulis et al. (2006) worked on designing a stand-alone hybrid PV–wind–battery energy system by focusing on the minimization of a 20 year total system cost. This cost is the sum of the components of capital and the maintenance fees. In addition, the solution is constrained by the load energy requirements

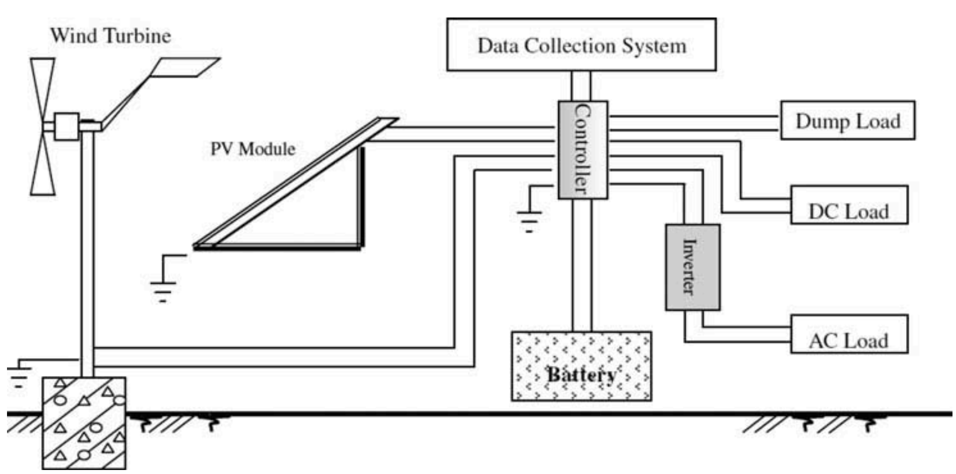

Fig. 1. Example of a hybrid PV–wind energy system.

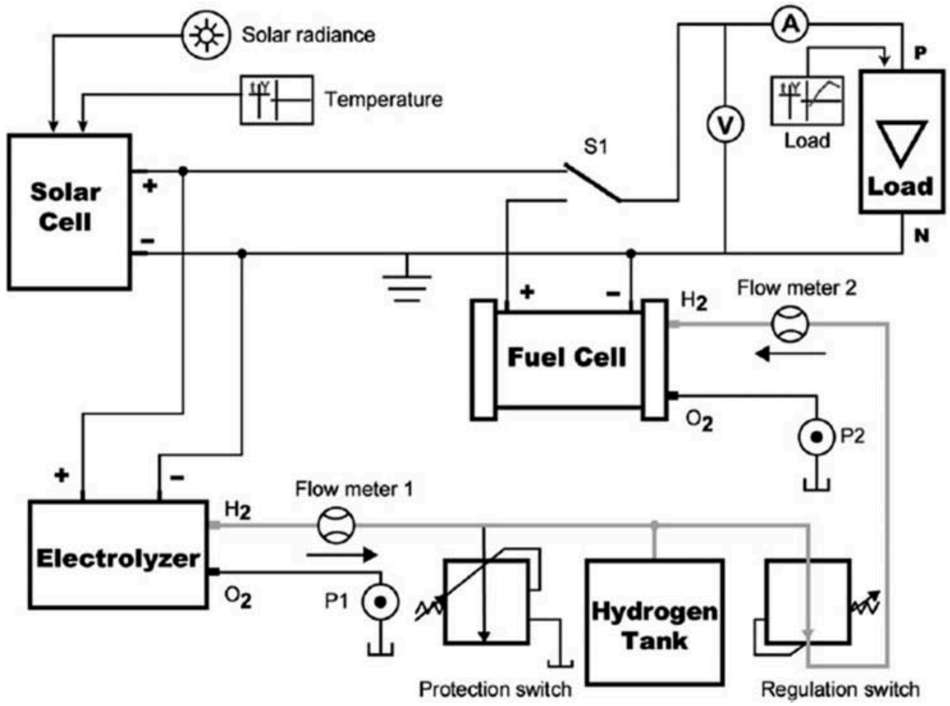

Fig. 2. Example of modeling of a PV–hydrogen FC energy system.

that need to be completely covered, that is, a zero load rejection. A genetic algorithm (GA) was used and it attained the global optimum faster than conventional optimization methods such as dynamic programming and gradient techniques. In addition, the result showed that a stand-alone hybrid PV–wind energy system is lower in cost than the exclusive usage of one energy source.

Weinstock and Appelbaum (2004) used Sequentiel Quadratic Programming for the optimization of solar field design. They divided their system into three sub-problems: energy maximization, minimization of the area field, and maximization of the solar unit area. They found that it is possible to increase the yearly energy by about 20% and a decrease of about 15% of the field area, compared to the current industrial standards in their area.

Ashok (2007) used nonlinear optimization for the design of a PV–wind–micro-hydro–diesel–battery system. They have found a micro-hydro/wind HES to be the most optimal combination from the cost perspective. In addition, it is the cleanest combination because of no diesel in the system. The system is tested in India (Western Ghats—Kerala).

Yang, Zhou, and Lou (2009) studied the design of hybrid solar–wind–battery energy systems. It was possible to calculate the system's optimum configurations while minimizing the annualized cost of the system, with respect to the required loss of power supply probability (LPSP). Five decision variables were considered in the optimization process: PV module number, PV module slope angle, wind turbine number, wind turbine installation height, and battery capacity. The results showed that it was possible from GA to attain the global optimum with relative computational simplicity. The proposed HES served as a power supply for a telecommunication relay station located in the southeastern coast of China.

Tina, Gagliano, and Raiti (2006) used a probabilistic approach based on a convolution technique for assessing long-term performance of a hybrid grid-connected PV–wind energy system. The system permitted the evaluation of different economic objectives such as electric contract demand, expected values of annual total cost, annual energy consumption, and others. The results of the analysis were not used only for the index of reliability calculation, but also allowed the documentation of other relationships between system parameters of interest.

Dufo-López and Bernal-Agustín used GAs for designing an optimal PV–diesel–battery system (Dufo-López and Bernal-Agustín 2005). GAs were used because of mixed-type variables: Boolean, integer, discrete. One GA served for selecting the components, while the second served for handling electric dispatch strategy (cycle charging or combined). They integrated the GAs into the HOGA tool. It appeared that the GA algorithm offered more precision than traditional methods because it was possible to get the number of PV panels, as well as their type, and the number of batteries in parallel, as well as their type. Also, HOGA was compared with the HOMER modeling tool (HOMER 2010), which they mentioned to be the best tool available. HOMER can optimize a wide range of energy components: PV generator, batteries, wind turbines, hydraulic turbines, AC generators, FCs, electrolyzers, hydrogen tanks, AC–DC bidirectional converters, and boilers. In addition, the loads can be of different type: AC, DC, and/or hydrogen or thermal loads. In addition, the tool is available free of charge. After the comparison, HOGA appeared to be faster and more precise than HOMER. This performance is attributed to the use of GAs by HOGA.

Mazhari et al. (2011) worked on the design of PV systems that are connected to storage units (compressed-air-energy-storage and super-capacitors), and also grid connected. They have used the *OptQuest* (Glover, Kelly, and Laguna 1999) tool for the design, which incorporates three metaheuristics Scatter Search, Tabu Search, and Neural Networks. They successfully obtained an optimal mixture of required capacities of the systems.

Giannakoudis et al. (2010) used the stochastic annealing optimization method for designing a PV–wind–FC–diesel system with consideration of the uncertainties. The resulting systems have a more robust response to external or system-inherent variations. Kaabeche, Belhamel, and Ibtiouen (2011) performed a case study on a PV–wind–battery system in Algeria. They have used a GA for system optimization. Zhao, Chen, and Blaabjerg (2009) proposed a GA for designing a wind farm by optimizing the production cost and system reliability. Senjyu et al. (2007) used a GA for the design of a PV–wind–battery–diesel system in Japanese islands. The results showed that HES systems reduce the cost by 10% in comparison with diesel generators.

Kaviani, Riahy, and Kouhsari (2009) used the particle swarm optimizer (PSO) for the design of a PV–wind–FC system. They demonstrated the importance of considering outage scenarios in the design. Hakimi and Moghaddas-Tafreshi (2009) used a PSO algorithm to optimize the design of a wind–FC system in a remote area in Iran. The designed system was sufficient to cover the demand of that area.

A limitation of the previous studies is that all of these tools optimize a single objective. They consider other objectives as constraints or variables. Nevertheless, the design of HESs is a multi-objective problem, and it should be modeled accordingly. The next section reviews multi-objective optimization (MOO) methods applied to the design of HES.

Multi-Objective Optimization for Hybrid Energy System Design

Dufo-López et al. were the first and only research group to our knowledge that have used MOO metaheuristic methods for HES design (Dufo-López, José, and Bernal-Agustín 2006, 2008). They developed a tool called HOGA (2010). According to their survey (Bernal-Agustín and Dufo-López 2009a,b), it appears that this is the only tool that uses an MOO metaheuristic for HESs. It supports, according to the user manual, the following objectives: total cost (NPC) versus CO_2 emissions, or total cost (NPC) versus unmet energy. It can handle various components: PV generator, batteries, wind turbines, hydraulic turbine, AC generators, FCs, electrolyzers, hydrogen tanks, rectifiers, and inverters. The loads can be AC, DC, and/or hydrogen.

First, Dufo-López, José, and Bernal-Agustín (2006) worked on the design of PV–wind–diesel–battery using MOO metaheuristic for the first time. The problem was composed of two objectives: minimization of cost through the useful life of the installation and the pollutant emissions while guaranteeing electrical energy supply at all times. The system generated a Pareto front composed of 50 solutions. The designer could choose the most appropriate solution, considering the costs and pollutant emissions, which demonstrate the practicality of using MOO methods.

Then, Dufo-López, José, and Bernal-Agustín (2008) used the same algorithm (Strength Pareto Evolutionary Algorithm, SPEA) for the same problem by adding more real-world complexity. They used a GA for a control strategy. Also, they added unmet load as a third objective and hydrogen-based FCs as an additional type of storage component. They developed a triple multi-objective design of a stand-alone PV–wind–diesel–hydrogen–battery HES. The system was located in Zaragoza, Spain. The SPEA algorithm was used for the simultaneous minimization of three objectives: the total NPC, pollutant emissions (CO_2), and the unmet load. The processing resulted in a Pareto front of 35 solutions from which the designer could select. Most of these solutions integrate wind and PV panels, and batteries for storage. Due to the high cost of a hydrogen storage component at that time, most of the solutions incorporated the exclusive use of batteries. The diesel fuel is highly priced in that location, which is why it was not part of the solutions.

There are some past studies applied to HES design. Dipama et al. proposed a new variant of a GA for the optimization of two different power plant problems (Dipama et al. 2010). First, they worked on the design of a cogeneration thermal plant. The objectives were the maximization of energy efficiency and minimization of cost rate. Second, they worked on the design of an advanced steam power station. The objectives were the maximization of both, the efficiency and the net power output of the plant. For both designs, the proposed GA has appeared to be reliable, powerful, and robust when compared with previous research studies.

Meza, Yildirim, and Masud (2009) examined a power generation expansion planning optimization problem. They proposed a multi-objective evolutionary programming algorithm (MEPA) for determining which, when, and where new generation units should be installed. A unit can be any one of the following: conventional steam units, coal units, combined cycle modules, nuclear plants, gas turbines, wind farms, and geothermal and hydro units. First, two objectives were considered: the minimization of investment and operation costs, and the environmental impact. Then, they added two other types (imports of fuel, and fuel price risks of the whole system) for a total of four objectives. The problem was nonlinear, mixed-integer, and considered as NP-hard. They concluded that the system offered good quality solutions (close to the real Pareto set) when optimizing two objectives. Furthermore, the system was able to provide solutions when handling four objectives. However, it was not possible to compare the results with previous work because no past studies considered more than two objectives for these kinds of problems.

Niknam et al. (2011) proposed a new multi-objective-modified honey bee mating optimization algorithm for the design of a PV–wind–FC grid-connected system. The proposed method showed better results than uni-objective optimization methods.

Ould et al. (2010) used a multi-objective GA for analyzing a hybrid PV–wind–battery energy system by minimizing the annualized cost system and the loss of power supply probability in remote areas in Senagal. They compared three configurations in their study.

Katsigiannis, Georgilakis, and Karapidakis (2010) used the NSGA-II multi-objective algorithm to design a PV–wind–FC–diesel–battery system. The results showed that PV–wind–battery is the most attractive combination from the cost and environmental point of view in Greece.

Summary and Future Trends

Energy System-Related Observations

As shown in Table 1, most of the systems are composed of PV and wind energy sources. These two energy sources match well together because both are intermittent and they complement each other. For example, sometimes there is no wind, but the weather is sunny; PVs will compensate, and vice versa. However, their complementary roles are sometimes deficient especially at night time because PV panels do not generate electricity. As a third component, hydrogen FCs are becoming more common within a stand-alone energy system framework. Previously, diesel and battery systems have been used. But FCs gained more popularity in the last couple of years because their prices are becoming more affordable, the technology is improving, and they are cleaner than batteries and diesel. The unused electricity generated from PV–wind is converted into hydrogen as an energy storage medium, which serves for operating FCs to regenerate electricity when needed (e.g., night time). Moreover, hydrogen surplus can be directly used for industrial or transportation purposes. Thus, PV and wind systems are the most common renewable systems; however, hydrogen systems are increasingly used in HESs.

Almost all of the HES projects involved a PV component to convert the solar energy source into electricity. But PV has a lower conversion efficiency than solar thermal systems in hotter areas. PV systems become even less efficient in hot areas like deserts because of the high temperature. Consequently, studies should consider the use of solar thermal systems as an alternative to PV systems to benefit from solar energy sources in such areas. Another interesting observation is that previously HES was typically designed as stand-alone systems in remote areas. Currently, HES tends to be integrated into existing grids, which requires more complex models.

Optimization-Related Observations

As shown in Table 1, simulation-based optimizations are declining because they require manual intervention for every run, which makes them time consuming, tedious, and error prone. On the other hand, metaheuristics such as GAs are more attractive for the design of HES for several reasons. They are completely automated, they can generate results in a faster manner, and can handle complex nonlinear models.

The energy research community has not fully utilized the most recent discoveries in the optimization field. There is a gap between the energy and optimization communities that should be bridged. This bridging will generate several positive impacts as follows when designing HES. First, HESs involve very complex optimization problems because of mixed-type variables, nonlinearity, and non-convexity, which make them difficult to solve with classical optimization methods; consequently, optimization metaheuristics such as GAs are more appropriate for optimal design of HESs.

All HES design projects involve multi-objectives such as cost and pollution minimization, efficiency maximization, among others. Therefore, multi-objective metaheuristics are more promising for these types of problems. Despite these advantages, only a few studies have been completed with MOO metaheuristics methods for energy system design. Even most of the state-of-the-art MOO methods have not been utilized yet. Comparative studies of state-of-the-art MOO methods can be found in Durillo et al. (2010) and Nebro et al. (2008). Moreover, multi-objective metaheuristics offer to HES designers multiple tradeoff solutions that are more practical and attractive for real-world engineering systems. The decision makers can select the solutions that best fit their needs. Furthermore, there are other newer MOO metaheuristics. For example, decision makers can be involved in the MOO process by selecting intermediate solutions or adding a priori knowledge to an HES problem. Consequently, the metaheuristic will converge faster, and generate solutions that will be more ad hoc to the needs of the decision makers. Such methods are called *interactive optimization* methods; more details can be found in Branke, Deb, and Miettinen (2008). Also, most past studies have not presented a comprehensive sensitivity analysis.

HES designs involve several uncertainties such as weather conditions, variations in the demand, and others. Therefore, HES design should always incorporate a sensitivity study to test the robustness of the HES. Alternatively, robust optimization methods can be used; these methods look for the most *robust* and optimal solutions at the same time. An extensive study of such methods can be found in Beyer and Sendhoff (2007).

Conclusions

HESs are attracting more attention because they can become more economical, environmentally cleaner, and can be installed in a distributed fashion. This literature review shows that most HESs are based on PV and wind energy sources because of their complementary roles. A challenge with solar and wind resources is their intermittency and not constantly available; usually they are complemented by diesel or batteries. However, diesel and batteries are decreasing while hydrogen systems are increasing. Hydrogen is cleaner than diesel and batteries, it is becoming cheaper, it can be reused for energy storage, and it regenerates electricity when needed. Another conclusion in this article is that previous studies focused on stand-alone systems usually installed in remote areas. Currently, the tendency is to have grid-connected HES. The simulation tools are more mature. However, several HES systems connected to the grid can generate grid congestion during peak hours. These congestion issues should be also considered when integrating multiple HES systems into a grid. Finding the optimal design of an HES is a complex task because it involves multiple objectives: a large number of variables, heterogeneous energy technologies, uncertainties such as weather and demand, and other factors.

This article has reviewed the current trends to designing optimal HESs. There are two main approaches for designing optimal HESs. The first is simulation-based optimization. It permits the variation of different variables or parameters of HESs in order to find an "optimal solution." These approaches require a designer's interaction for setting the parameters in order to find an "optimal" design. Therefore, this approach is arduous and time consuming. Moreover, every simulation generates only one solution. Furthermore, there is no automated support for helping or guiding the designer toward the

Table 1. Recapitulates the Simulation and Optimization Methods Found for the Design of HES.

Research	Year	Solar	Wind	Fuel cell	Diesel	Battery	Other	Stand-alone	Grid connected	Simulation only	Multi-objective	Unique objective	Optimization	Tools	Optimization methods
Borowy and Salameh	1996	X	X			X		X		X					
McGowan and Manwell	1999	X	X		X	X		X		X				Hybrid 2	
Karaki, Chedid, and Ramadan	1999	X	X			X		X		X				Probabilistic model	
Elhadidy	2002	X	X		X			X		X					
Weinstock and Appelbaum	2004	X						X				X	X		SQP
Wies et al.	2005	X			X	X				X				Simulink, HOMER	
Dufo-López and Bernal-Agustín	2005	X			X	X		X				X	X	HOGA, HOMER	GA
Koutroulis et al.	2006	X	X			X		X				X	X	HOMER	GA
Tina, Gagliano, and Raiti	2006	X	X						X			X	X		Probabilistic
Nfah, Ngundam, and Tchinda	2007	X	X		X	X		X		X					
Shaahid and Elhadidy	2007	X			X	X		X		X				HOMER	
Ashok	2007	X	X		X	X	Hydro	X				X	X		NL
Senjyu et al.	2007	X	X	X	X			X				X	X		GA
Diaf et al.	2008	X	X			X		X		X					
Dalton, Lockington, and Baldock	2008	X	X		X	X		X		X				HOMER and HYBRIDS	
Himri et al.	2008		X		X				X	X				HOMER	
Dufo-López, José, and Bernal-Agustín	2008	X	X	X	X			X			X		X		GA, evol. strategy
Li et al.	2008	X		X		X		X			X		X	HOGA	GA
Yang, Zhou, and Lou	2009	X	X			X		X				X	X		GA
Shaahid and El-Amin	2009	X			X	X		X		X				HOMER	

Dufo-López, Bernal-Agustín, and Mendoza	2009	X	X	X					X	X					
Meza, Yildirim, and Masud	2009		X				X	X			X		X		Evolutionary (PEAS)
Zhao, Chen, and Blaabjerg	2009		X					X				X	X		GA
Kaviani, Riahy, and Kouhsari	2009	X	X	X				X	X						PSO
Hakimi and Moghaddas-Tafreshi	2009		X	X				X				X	X		
Mondal and Denich	2010	X	X				Hydro		X	X				HOMER	
Prodromidis and Coutelieris	2010	X	X	X			Hydro	X	X	X				HOMER	
Katsigiannis, Georgilakis, and Karapidakis	2010	X	X	X	X	X		X			X				NSGA-II
Glover, Kelly, and Laguna	1999	X					X		X			X	X	OptQuest	Scatter search, tabu, NN
Giannakoudis et al.	2010	X	X	X	X				X			X	X		Stochastic annealing
Kaabeche, Belhamel, and Ibtiouen	2011	X	X			X		X				X	X		GA
Niknam et al.	2011	X	X	X					X		X		X		Modified honey bee mating
Balamurugan, Ashok, and Jose	2009	X	X			X	Biomass	X		X				HOMER	

optimum. The second approach uses optimization methods for designing HESs. The current trend is the use of metaheuristic algorithms for HES optimization design because they obtain automatically optimal or close to optimal solutions. They can handle a high number of mixed-type variables (i.e., real vs. discrete variables). Furthermore, metaheuristics can handle complex problems such as energy design systems that are not linear, nor convex. Therefore, metaheuristics are more suitable for solving hybrid design energy problems. In addition, all HESs involve multiple competing objectives such as cost minimization and energy maximization that can be solved by MOO metaheuristics. MOO metaheuristics generate multiple tradeoff solutions that are more practical and attractive for real-world engineering systems. Despite these advantages, this literature review has shown that very limited work has been conducted in the past with MOO metaheuristics for energy system design. Furthermore, the used MOO metaheuristics were not state of the art. Therefore, the design of optimal HESs requires more interaction between both energy and MOO research communities to fill this gap. Other more recent MOO metaheuristics methods should be explored such as MOO robust optimization and MOO interactive optimization methods. Robust optimization targets optimal and robust solutions at the same time, while interactive optimization takes input from decision makers while searching optimal solutions.

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