Renewable and Sustainable Energy Reviews 15 (2011) 1753–1766

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

# Optimization methods applied to renewable and sustainable energy: A review

R. Baños[a], F. Manzano-Agugliaro[b,*], F.G. Montoya[b], C. Gil[a], A. Alcayde[b], J. Gómez[c]

[a] Department of Computer Architecture and Electronics, University of Almería, 04120 Almería, Spain
[b] Department of Rural Engineering, University of Almería, 04120 Almería, Spain
[c] Department of Languages and Computation, University of Almería, 04120 Almería, Spain

ARTICLE INFO

*Article history:*
Received 23 November 2010
Accepted 27 December 2010

*Keywords:*
Renewable energy systems
Optimization
Multi-criteria decision analysis
Design
Planning
Control

ABSTRACT

Energy is a vital input for social and economic development. As a result of the generalization of agricultural, industrial and domestic activities the demand for energy has increased remarkably, especially in emergent countries. This has meant rapid grower in the level of greenhouse gas emissions and the increase in fuel prices, which are the main driving forces behind efforts to utilize renewable energy sources more effectively, i.e. energy which comes from natural resources and is also naturally replenished. Despite the obvious advantages of renewable energy, it presents important drawbacks, such as the discontinuity of generation, as most renewable energy resources depend on the climate, which is why their use requires complex design, planning and control optimization methods. Fortunately, the continuous advances in computer hardware and software are allowing researchers to deal with these optimization problems using computational resources, as can be seen in the large number of optimization methods that have been applied to the renewable and sustainable energy field. This paper presents a review of the current state of the art in computational optimization methods applied to renewable and sustainable energy, offering a clear vision of the latest research advances in this field.



**Contents**



*Abbreviations:* ABCO, artificial bee colony optimization; ACO, ant colony optimization; ANN, artificial neural networks; DE, differential evolution; EA, evolutionary algorithm; EDA, estimation of distribution algorithm; GA, genetic algorithms; GRASP, greedy randomized adaptive search procedures; GTS, genetic tabu search; HC, hill climbing; HBMO, honey bee mating optimization; I-GA, immune genetic algorithm; ILP, integer-linear programming; ILS, iterated local search; LP, linear programming; LR, Lagrangian relaxation; MA, memetic algorithms; MINLP, mixed-integer non-linear programming; MOEA, multi-objective evolutionary algorithm; MOGLS, multi-objective genetic local search; MOSA, multi-objective simulated annealing; MOSATS, multi-objective simulated annealing and tabu search; MOTS, multi-objective tabu search; M-PAES, memetic-PAES; NLP, non-linear programming; NMS, Nelder–Mead Simplex; NSGA/NSGA-II, non-dominated sorting genetic algorithm/-II; PAES, Pareto archived evolution strategy; PESA/PESA-II, Pareto envelope-based selection algorithm/-II; PR, path relinking; PSA, Pareto simulated annealing; PSO, particle swarm optimization; QP, quadratic programming; SA, simulated annealing; SFGA, single front genetic algorithm; SPEA/SPEA2, strength Pareto evolutionary algorithm/2; SS, scatter search; TS, tabu search; VNS, variable neighborhood search.

* Corresponding author. Tel.: +34 950015396; fax: +34 950015491.
*E-mail addresses:* rbanos@ual.es (R. Baños), fmanzano@ual.es (F. Manzano-Agugliaro), pagilm@ual.es (F.G. Montoya), cgilm@ual.es (C. Gil), aalcayde@ual.es (A. Alcayde), jgomez@ual.es (J. Gómez).

1364-0321/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.rser.2010.12.008

## 1. Introduction

With the rapid development of the global economy, energy requirements have increased remarkably, especially in emergent countries. The realization that fossil fuel resources required for the generation of energy are becoming scarce and that climate change is related to carbon emissions to the atmosphere has increased interest in energy saving and environmental protection [1]. The first strategy to reduce dependence on fossil resources is based on reducing energy consumption by applying energy savings programs focused on energy demand reduction and energy efficiency in industrial [2] and domestic [3] fields spheres.

A second strategy to achieve this goal consists of using renewable energy sources, not only for large-scale energy production, but also for stand-alone systems [4]. Renewable energy technologies are known to be less competitive than traditional electric energy conversion systems, mainly because of their intermittency and the relatively high maintenance cost. However, renewable energy sources have several advantages, such as the reduction in dependence on fossil fuel resources and the reduction in carbon emissions to the atmosphere. Furthermore, renewable energies avoid the safety problems derived from atomic power [5], which is why, from the social point of view, it has become more desirable to adopt renewable energy power plants [6]. An important decision for governments and businesses is whether or not to establish renewable energy systems in a given place, and to decide which renewable energy source or combination of sources is the best choice. Several authors have evaluated the main renewable energy technologies taking into account sustainability indicators, such as Evans et al. [7] who compared wind power, hydropower, photovoltaic and geothermal energy taking into account the price of generated electricity, greenhouse gas emissions during the full life cycle of the technology, availability of renewable sources, efficiency of energy conversion, land requirements, water consumption and social impacts. Evans et al. concluded that wind power has the lowest relative greenhouse gas emissions, the least water consumption demands and the most favorable social impacts, but it requires more land and has high relative capital costs [7]. Lund et al. [8] analyzed strategies for a sustainable development of renewable energy taking into account three major technological changes: energy savings on the demand side, efficiency improvements in energy production, and the replacement of fossil fuels with various sources of renewable energy. Others recent studies that evaluate energy, economics and environmental impacts of renewable energy systems include those presented by Hepbasli [9] and Varun et al. [10].

The improvement of renewable energy technologies will assist sustainable development and provide a solution to several energy related environmental problems. In this sense, optimization algorithms constitute a suitable tool for solving complex problems in the field of renewable energy systems. Fig. 1 shows an exponential evolution in the number of research papers that use optimization algorithms in the renewable energy sources described in this paper, using Scopus database. Some authors have reviewed different types of models such as renewable energy models, emission reduction models, energy planning models, energy supply-demand models, forecasting models, and control models using optimization methods [11], but many researchers are continuously proposing and applying new methods in the field of renewable energy. For this reason, this paper presents an updated review of the optimization methods that have recently been applied to renewable energies.

## 2. Single and multi-objective optimization: a brief overview

In mathematics, optimization is the discipline concerned with finding inputs of a function that minimize or maximize its value, which may be subjected to constraints [12]. Combinatorial optimization is a branch of optimization which is concerned with the optimization of functions with discrete variables [13]. Computational optimization can be defined as the process of designing, implementing and testing algorithms for solving a large variety of optimization problems. Computational optimization includes the disciplines of mathematics to formulate the model, operations research to model the system, computer science for algorithmic design and analysis, and software engineering to implement the model. Nowadays, researchers can solve real-life problems that in the past were thought to be unsolvable thanks to new technological developments in algorithms and computer hardware.

Despite its name, optimization does not necessarily mean finding the optimum solution to a problem, since it may be unfeasible due to the characteristics of the problem, which in many cases are included in the category of NP-hard problems [14]. Yet, for optimization problems that are NP-hard, no polynomial time algorithm exists, i.e. the algorithms used might need exponential computation time in the worst case to obtain the optimum, which leads to computation times that are too high for practical purposes. As a result, in recent decades many authors have proposed approximate methods, including heuristic approaches and artificial neural networks (ANN), to solve these problems instead of using traditional optimization methods, such as linear-programming (LP), Nelder–Mead Simplex (NMS) method, Lagrangian relaxation (LR), quadratic programming (QP), etc. Heuristic methods can be seen as simple procedures that provide satisfactory, but not necessarily optimal, solutions to large instances of complex problems rapidly. Meta-heuristics are generalizations of heuristics in the sense that they can be applied to a wide set of problems, needing few modifications to be adapted to a specific case [15]. In some cases, the complexity of the problems to solve is so high that even heuristic and meta-heuristic methods are not able to obtain accurate solutions in reasonable runtimes. In these cases parallel processing becomes an interesting way to obtain good solutions in reduced runtimes [16].

The most used way to classify meta-heuristic algorithms is based on trajectory methods vs. population-based methods, although other possible classifications are memory-based vs. memory-less methods, nature-inspired vs. non nature-inspired, etc.

- Trajectory meta-heuristics are those that use a single solution during the search process and the outcome is also a single optimized solution. Most of them are extensions of simple iterative improvement procedures that incorporate techniques that enable the algorithm to escape from local optima. The main trajectory-based meta-heuristics include: hill climbing (HC), simulated annealing (SA), tabu search (TS), greedy randomized adaptive search procedures (GRASP), variable neighborhood search (VNS), iterated local search (ILS), etc. [15–17].
- Population-based meta-heuristics use a population of solutions which evolve during a given number of iterations, also returning a population of solutions when the stop condition is fulfilled. The main population-based meta-heuristics include: genetic algorithms (GA) and evolutionary algorithms (EA), scatter search (SS), path relinking (PR), memetic algorithms (MA), ant colony optimization (ACO), particle swarm optimization (PSO), estimation of distribution algorithm (EDA), differential evolution (DE), artificial bee colony optimization (ABCO), etc. [15–17].

On the other hand, it should be noted that to date most computational optimization methods have focused on solving single-objective problems, including constraints in some cases. Nevertheless, there exist a large number of applications that require the simultaneous optimization of several objectives which

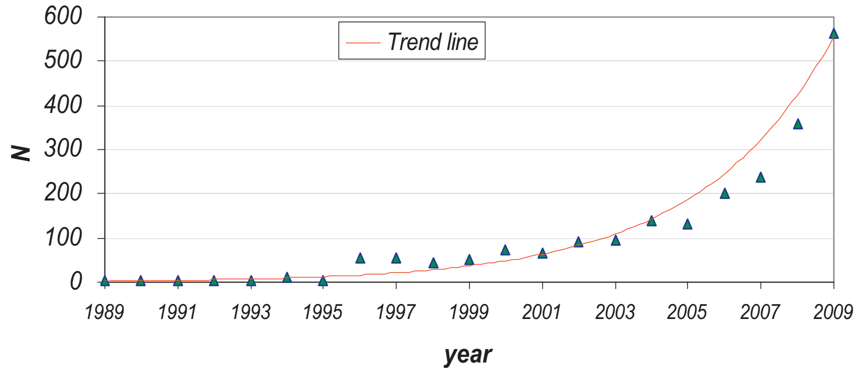


**Fig. 1.** Number of articles using optimization algorithms applied to renewable energies in the last 20 years (reviews were not taken into account).

are often in conflict, and so some authors have proposed multi-objective algorithms. These multi-objective approaches are often divided into two main categories: aggregate weight functions and Pareto-based optimization methods. Aggregating functions consist of combining all the objectives to optimize in a single mathematical function, where the relative importance of each objective is adjusted according to relative weights [18]. Despite its simplicity, this approach has several drawbacks, such as that it is very difficult to adjust the weights of the objectives to optimize, especially when they have different scales. Further, this approach only returns a single solution as a result of the search process, which becomes an important limitation in the decision-making process, where the decision maker must select one solution from several alternatives.

The drawbacks of aggregating functions have been solved using Pareto-based multi-objective optimization [19], which establishes relationships among solutions according to the Pareto-dominance concept. Given a multi-objective optimization problem with $K \geq 2$ objectives to optimize, instead of giving a scalar value to the objective function $f_{1...K}(s)$ of solution $s$, a partial order is defined according to Pareto-dominance relationships. It is said that solution $s_1$ dominates another $s_2$ when $s_1$ is better than $s_2$ in at least one objective, and not worse in the others. It is said that two solutions, $s_1$ and $s_2$ are indifferent if neither dominates the other one. The set of non-dominated solutions constitute the so-called Pareto optimal set, which usually contains not one solution, but several. As all the objectives are equally important, the aim of multi-objective optimization is to find this entire set or a representative sample of it.

A large number of multi-objective meta-heuristics have been presented in recent decades, and they can also be classified into the categories of trajectory methods and population-based methods. Trajectory methods include the Pareto archived evolution strategy (PAES), multi-objective simulated annealing (MOSA), etc. Population-based meta-heuristics include the multi-objective tabu search (MOTS), non-dominated sorting genetic algorithm (NSGA/NSGA-II), Pareto simulated annealing (PSA), single front genetic algorithm (SFGA), strength Pareto evolutionary algorithm (SPEA/SPEA2), Pareto envelope-based selection algorithm (PESA/PESA-II). Some authors have also proposed hybrid approaches that combine aspects of two or more methods, such as genetic tabu search (GTS), multi-objective genetic local search (MOGLS), memetic-PAES (M-PAES), multi-objective simulated annealing and tabu search (MOSATS), etc. [20,21].

Taking into account information from the ISI web of knowledge, Fig. 2 shows the distribution by country of papers that use optimization algorithms mentioned in this section, applied to renewable energy. It is observed that researchers from 10 countries cover this research line.

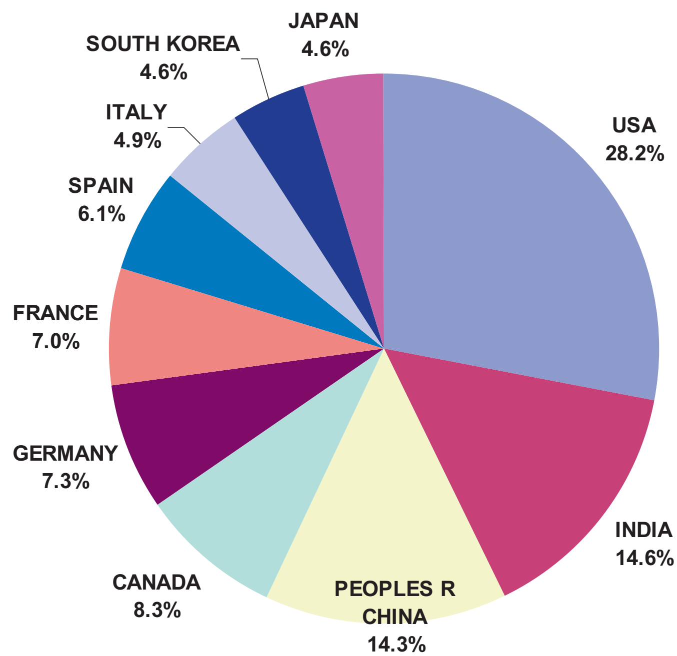


**Fig. 2.** Distribution by country of research papers published using optimization algorithms studied in this paper applied to renewable energies.

## 3. Optimization methods applied to renewable and sustainable energy

Energy resources are very important form an economic and political perspective for all countries, which is why technological change in energy systems is a very important and inevitable factor that researchers need to deal with [22]. In the many papers propose optimization methods for solving problems found in renewable energy systems. A review of these methods from the point of view of design, planning and control is provided below.

Taking into account the increasing worldwide demand for energy around the world, the expansion of distributions networks has become a problem of primary interest. Due to the important investment costs of creating a renewable energy structure, a primary interest from the point of view of the design and long-term planning of energy systems is to select the best alternative among the different renewable energy systems. Community-scale renewable energy systems planning is an important problem consisting of justifying the allocation patterns of energy resources and services, formulation of local policies regarding energy consumption, economic development and energy structure, and analysis of interactions among economic cost, system reliability and energy-supply security. Some authors have solved this complex problem by applying interval linear programming (ILP), chance-constrained programming, and mixed integer-linear programming (MILP) techniques to obtain solutions that can provide desired energy resource/service allocation and capacity-expansion plans with a minimized system cost, maximized system reliability and maximized energy security [23]. Soroudi et al. [24] presented a long-term dynamic multi-objective planning model for distribution network expansion along with distributed energy options which, using an immune genetic algorithm-based (I-GA) algorithm, optimizes costs and emissions by determining the optimal schemes of sizing, placement and dynamics of investments on distributed generation units and network reinforcements over the planning period. Kahraman et al. [25] analyzed the use of fuzzy-based multicriteria decision-making procedures in order to determine the most appropriate renewable energy alternative. Connolly et al. [26] reviewed the main computer tools for analyzing the integration of renewable energy into various energy-systems under different objectives. Some authors have analyzed the performance of mixed-integer programming (MIP), GA, SA and TS for solving the problem of minimum cost expansion of power transmission networks under carbon emission trading programs [27,28]. Zangeneh et al. [29] show that only a few renewable energies have proven to be competitive to date, while their economic viability is also limited to certain regions of the world. These authors propose a Pareto-based multi-objective optimization algorithm for optimal planning schemes by considering several generation technologies: photovoltaic, wind turbine, fuel cell, micro turbine, gas turbine, and reciprocal engine. Cai et al. [30] proposed an optimization method that integrates ILP, two-stage programming and superiority–inferiority-based fuzzy-stochastic programming for long-term renewable energy management planning with the aim of generating decision alternatives and thus helping decision makers identify desired policies under various economic and system-reliability constraints. Kowalski et al. [31] evaluated several renewable energy scenarios according to different sustainability criteria. AlRashidi and EL-Naggar [32] applied a PSO algorithm for annual peak load forecasting in an electrical power system with the aim of minimizing the error associated with the estimated model parameters. Dicorato et al. [33] applied a LP optimization procedure based on the energy flow optimization model for evaluating the contribution of distributed-generation production and energy-efficiency actions taking into account the exploitation of primary energy sources, power and heat generation, emissions and end-use sectors. Other researchers have focused their efforts on designing heuristic optimization methods for cost-effective energy conversion systems [34].

The importance of using new optimization techniques for short-term energy planning is due to the existence of multiple uncertainties [35,36]. In a scenario of large-scale penetration of renewable production, it is fundamental that the electric system has appropriate means to compensate the effects of the variability and randomness of the wind, solar and hydro power availability. There are many optimization problems related to energy in general which deal with optimization techniques, such as the prediction of energy demands using ANN [37]. Mitchell et al. [38] presented a simulator of a renewable energy system in both grid-connect and stand-alone modes, containing wind, solar, energy storage and stand-by plants, which is able to calculate energy flows and optimize the scheduling of the stand-by plant or grid connection. Other researchers have developed preprocessing techniques and heuristic algorithms for real problems in timetabling and labor scheduling, obtaining excellent results [39]. Energy planning problems are complex problems with multiple decision makers and multiple criteria. In the literature there are some reviews about multicriteria decision-making methods for renewable energy problems [40–42]. Alarcón-Rodríguez et al. [43] reviewed the state-of-the-art in multi-objective distributed energy resources planning, and concluded that demand side management and load controllability will gain prominence in a future where the impacts of energy use will be managed more carefully.

From the point of view of control, one of the main problems is that of determining the impact of renewable energy on power systems, especially on distribution networks. Renewable energy sources are mainly used in the electrical sector. Electricity is not a storable commodity, i.e. it is necessary to produce the requested quantity and distribute it through the system in such a way as to ensure that electricity supply and demand are always evenly balanced. Franco and Salza [44] applied several optimization methods for solving the problem of new renewable energy sources penetration and congestion management. Sood and Singh [45] presented an optimal model of congestion management for the deregulated power sector that dispatches the pool in combination with privately negotiated bilateral and multilateral contracts while maximizing social benefit. Niknam and Firouzi [46] proposed a hybrid method that combines NMS and PSO, whose results outperformed those obtained by other population-based algorithms such as original PSO, honey bee mating optimization (HBMO), ANN, ACO, and GA. The utilization of fluctuating renewable energy sources is increasing, but how to integrate these resources into the energy systems is a difficult question. Ostergaard [47] reviewed and subsequently applied several optimization criteria to an energy system model with the aim of analyzing how to use heat pumps for the integration of wind power. Niknam et al. [48] proposed an algorithm based on fuzzy adaptive PSO to solve the optimal operation management of distribution networks including fuel cells power plants which obtain good results in comparison with GA, PSO, DE, ACO and TS. In order to improve energy systems, some researchers are investigating how to store energy efficiently, which is an important problem whose solution would effectively disassociate the timing of supply and delivery. Yongping et al. [49] analyzed a multi-objective optimization of load dispatch of power systems including renewable energy and $CO_2$ capture and storage technologies. Other researchers have proposed models for optimal bidding strategy for a hybrid system of renewable power generation and energy storage [50].

The advantages of renewable energy resources are not limited to the generation of energy, they also include using it for multi-purpose functions such as water pumping. Water distribution is an optimization problem with important environmental derivations [51–54]. Some authors have analyzed the use of solar photovoltaic pumps, windmill pumps and biogas based dual fuel engine pumps for irrigation water pumping [55], while others have used wind turbine water-pumping applications either by direct pumping through mechanical means, or indirectly by generating electric power to drive pumps [56]. Further, water supply systems [51,54] frequently present high-energy consumption values, which correspond to the major expenses of these systems. Energy costs are a function of their real consumption and of the variability of the daily energy tariff. Vieira and Ramos [57] optimized operational planning for wind-hydro hybrid water supply systems. Further, there has been considerable interest in the design of renewable-energy-based greenhouses. Chinese et al. [58] determined under which conditions the combination of a floor-heating-based greenhouse with a waste-to-energy plant can be profitable using a mixed integer optimization model.

This review goes on to offer an overview of the latest research advances in optimization algorithms for renewable energy classified by different energy sources.

### 3.1. Wind power

Wind is one of the most promising sources of alternative energy. Recently, Hernández et al. [59] demonstrated that wind is a periodical phenomenon for large geographical areas like Mexico. The benefits of past research and development in the wind energy sector have been clearly demonstrated by the increasing sizes of turbines and the lower prices per installed production capacity of electricity [60]. There are studies that demonstrate the potential wind power around the world [61]. Trends in wind power include new growth in off shore development, the growing popularity of distributed, small-scale grid-connected turbines, and new wind projects in a much wider variety of geographical locations around the world. Many researchers are continuously developing new strategies for optimal design and operation of wind energy systems [62]. However, wind energy systems may not be technically viable in all locations because of low wind speeds and the fact that it is more unpredictable than solar energy. Areas where winds are stronger and more constant, such as offshore and high altitude sites, are preferred locations for wind farms. The operational scheme of wind energy systems, an accurate estimation of wind speed distribution, the site selection of wind farms, and the operations management of wind power conversion systems are critical aspects that determine wind energy potential. However, the investment decision on generation capacity of a wind park is difficult when wind studies or data are neither available nor sufficient to provide adequate information for developing a wind power project. Some papers have analyzed in detail how to determine the probable wind power availability at a given site according to historical wind velocity data, and its capacity to meet a target demand [63]. Li et al. [64] applied the Bayesian model averaging in modelling long-term wind speed distributions. Zhao et al. [65] proposed a GA where the main components of a wind farm and key technical specifications are used as input parameters and the electrical system design of the wind farm is optimized in terms of both production cost and system reliability.

Another primary interest for researchers of wind power is related to the optimal design of wind farms. In particular, two important problems are often considered: the optimal design of wind turbines and the wind farm layout.

In reference to wind turbine design, trends include new growth in off-shore development, the growing popularity of distributed, small-scale grid-connected turbines, and new wind projects in a much wider variety of geographical locations around the world and within countries. The power output of a turbine is a function of the density of the air, the area swept out by the turbine blades and the cube of the wind speed. As the generation of wind energy is relatively new, the area of improvement in power quality is still open, which is why some authors have centred their interest on optimizing the turbine settings in order to maximize their performance. Numerous metrics are used to measure the power quality of a wind turbine, such as the power factor, reactive power, harmonic distortion, etc. Firms continue to increase average turbine sizes and improve technologies, such as with gearless designs [66]. Benini and Toffolo [67] presented a multi-objective evolutionary algorithm (MOEA) for the optimization of the geometrical parameters of the rotor configuration of stall-regulated horizontal-axis wind turbines with the aim of achieving the best trade-off performance between the total energy production per square meter of wind park and cost. Maalawi and Negm [68] presented an optimization model for the design of a typical blade structure of horizontal-axis wind turbines where the optimization variables are chosen to be the cross-sectional area, radius of gyration and length of each segment, and the optimal design is pursued with respect to maximum frequency design criterion. Other authors [69] simplified the design of wind turbine systems by removing any active electronic part (power and control) then constructing a low-cost fully passive structure. There has been increasing interest in the optimal design of laminated composite shell structures, especially wind turbine blades. For instance, Lund and Stegmann [70] solved this problem using as optimization algorithm the method of moving asymptotes proposed by Svanberg [71]. A review of methods applied to the optimal design of wind turbine blades was presented by Jensen et al. [72]. Li et al. [73] optimized the ranges of gearbox ratios and power ratings of multihybrid permanent-magnet wind generator systems by using a GA. Kusiak et al. [74] presented a MOEA for evaluating wind turbine performance, where the objective to maximize is the wind power output, while minimizing the vibration of the drive train and of the tower. Roy et al. [75] applied a new methodology for optimum sizing of the rotor and other components of a stand-alone wind-battery system. Other authors [76] optimized wind turbine blades, where shape parameters, including chord, twist and relative thickness are adjusted with the objective of minimizing the cost of energy which is calculated from the annual energy production and the cost of the rotor. Fuglsang and Thomsen [77] proposed a numerical optimization algorithm together with an aero elastic load prediction code and a cost model for site-specific design of wind turbines where cost of energy is minimized. Fuglsang et al. [78] presented a method for minimum energy cost where numerical optimization and aero elastic calculations are combined. Kusiak and Zheng [79,80] optimized the power produced by wind turbines by combining data mining and evolutionary computation. Other authors have proposed decision analysis techniques, including mixed-integer nonlinear programming (MINLP), for determining the optimum capacity taking into account uncertainties arising from wind speed distribution and power–speed characteristics [81]. As wind turbines are used to tap the potential of wind energy, the reliability of the turbine is critical to extract the maximum amount of energy from the wind. Hameed et al. [82] offered a review of the techniques, methodologies and optimization algorithms developed to monitor the performance of wind turbines and for early fault detection to avoid catastrophic conditions due to sudden breakdowns. Technically, wind turbine capacity has been improved to high levels. However, electricity cannot be generated at all wind speeds and so there are some limits related to cut-in and cut-out data. One of the main problems in wind engineering is that estimating output data of wind turbines depends on wind speed and system values, which is why some researchers have used fuzzy logic modelling for wind turbine power curve estimation [83]. Shimizu et al. [84] presented a study of the flapping wind power generator which extracts energy via the flutter phenomenon, where the aim is to optimize both the power and the efficiency of the system using a multi-objective adaptive neighboring search.

On the other hand, wind farm layout consists of determining the optimum positions of wind turbines within the farm in order to maximize energy production [85]. Grady et al. [86] presented a GA to determine the optimal placement of wind turbines for maximum production capacity while limiting the number of turbines installed and the acreage of land occupied by each wind farm. Emami and Noghreh [87] solved this problem with a new coding and also a novel objective function in GA which performs better that other previously proposed approaches in terms of control of the cost, power, and efficiency of the wind farm. Serrano et al. [88] implemented an EA for the optimum wind farm configuration problem which is driven by an integral wind farm cost model based on the cumulative net cash flow value throughout the wind farm's lifespan. Kusiak and Song [89] proposed a MOEA for wind turbine placement based on wind distribution with the aim of both maximizing the wind energy capture and minimizing a second objective, namely an index that determines constraint violations. The related problem of wind turbine selection, consists of selecting the best turbine combination from a given list of available turbines. Herbert et al. [90] analyzed the performance, failure and reliability of a wind farm using a Pareto-based analysis. Mustakerov and Borissova [91] proposed a MINLP optimization method to determine the optimal type, number and placement of wind turbines considering the given wind conditions and wind park area.

One of the main problems related to wind generation consists of forecasting the output with uncertainties. These uncertainties pose a challenge while computing optimal bids necessary for participating in the day-ahead unit commitment process. Some authors solved this problem by applying fuzzy optimization techniques, with the aim of both maximizing benefits while minimizing risks considering forecast uncertainties [92]. Kusiak and Li [93] validated a methodology for prediction of wind speed at a selected location based on the data collected at neighboring locations. Abdel-Aal et al. [94] dealt with the problem of wind speed forecast by using abductive networks, which offer the advantages of simplified and more automated model synthesis and transparent analytical input-output models than other machine learning approaches reported in the literature. Despite the research into predicting wind conditions, the magnitude of power fluctuations at large off-shore wind farms can be said to have a significant impact on the control and management strategies of their power output. Pinson et al. [95] investigated the use of statistical regime-switching models, thus demonstrating that the magnitude of fluctuations of off-shore wind power cannot be considered as being only influenced by the generation level. Some authors have tackled the problem of discontinuity in the generation of wind power. Zhang and Wirth [96] proposed an online heuristic for short-term energy management of a wind power plant with battery storage in order to offset variations in power output to the external grid in which decision making is independent of historical wind data and forecasts. Due to the intermittent nature of wind power generation, many new problems arise when infusing wind power into power network with conventional generators. Boqiang and Chuanwen [97] discussed how to manage risk in the electric market using wind power, and evaluated in detail different optimized algorithms for this purpose, including a direct search method, PSO, SA, GA, and a scenario construction method. The control problem of a wind turbine involves determining rotor speed and tip-speed ratio to maximize power and energy capture from the wind. This problem has also been solved with heuristic approaches, including PSO [98]. Although wind generation does not produce harmful emissions, its effect on the thermal generation dispatch can actually cause an increase of emissions, especially during low or medium power demand periods in the day. Kuo [99] presented a multi-objective energy dispatch that considers environment and fuel cost. Ko and Jatskevich [100] used a fuzzy-linear-quadratic regulator controller for a wind-hybrid power generation system to enhance power quality which is effective against disturbances caused by the wind speed and load variations. Kusiak et al. [101] presented a multi-objective model for intelligent wind turbine control based on integrating data mining, model predictive control and evolutionary computation considering five different objectives and taking into account wind speed, turbulence intensity, and electricity demand as control factors. Li et al. [102] tackled the optimal design problem of integrating the number of actuators, the configuration of the actuators and the active control algorithms in buildings excited by strong wind force using a multi-level GA.

### 3.2. Solar energy

Solar energy is radiant energy that is produced by the sun. In many parts of the world, direct solar radiation is considered to be one of the best prospective sources of energy. The main ways to convert solar radiation into energy are active and passive solar design. Passive solar design is often based on the optimal design of buildings that capture the sun's energy in order to reduce the need for artificial light and heating. Regarding passive solar systems, a primary interest for researchers in solar energy is related to the design and optimization of solar energy homes [103]. Improving energy efficiency in buildings is a major priority worldwide. The measures employed to save energy vary in nature, and the decision maker is required to establish an optimal solution, taking into account multiple and usually competing objectives such as energy consumption, financial costs, environmental performance, etc. [104,105]. Active solar design is based on water heating converting solar radiation into heat using photovoltaic panels and solar cells to convert the solar radiation into energy.

In order to design both active and passive solar energy systems, radiation data are needed for the studied location. Solar radiation is usually measured by means of radiometric station nets with a low spatial resolution. To estimate the radiation some interpolation/extrapolation techniques are often used, but they are valid for places where the spatial variability of radiation is not significant and are less accurate if there are complex areas of terrain between the radiometric stations. Bosch et al. [106] presented an artificial intelligence technique based on ANN for calculating solar radiation levels over complex mountain terrains using data from only one radiometric station. Other algorithms applied to the forecast of solar irradiation include ANN [107,108] and neuro-fuzzy inference systems [109]. Despite huge development in predicting solar radiation data, there is a gap in extraction of pertinent information from such data, which is why some methods, including ANN [110], have been proposed for identifying and optimizing the statistics representing solar radiation availability.

Due to the intermittent nature of solar energy, energy storage is needed in a stand-alone photovoltaic system for the purpose of ensuring continuous power flow. The large-scale utilization of this form of energy is possible only if effective technology can be developed for its storage with acceptable capital and running costs [111]. The industry of grid-connected photovoltaic solar power has been responding to price declines and rapidly changing market conditions by consolidating, scaling up and moving into project development [66]. Kalogirou [112] solved the problem of maximizing the economic benefits of a solar-energy system using ANN and GA. ANN are trained to learn the correlation of collector area and storage-tank size on the auxiliary energy required by the system from which life-cycle savings can be estimated, while GA are then employed to estimate the optimum size of these two parameters for maximizing life-cycle savings. Aronova et al. [113] proposed an optimization model for determining the energy generated by tracking photoelectric power modules, while also estiming the optimal variant of solar module arrangement for different locations, and the ground area required by a single tracking photoelectric power module of given size. Klychev et al. [114] presented a study about the optimization of the geometric parameters of the parabolic-cylinder-receiver system of thermal power plants, and they conclude that the optimal opening angles of the parabolic-cylindrical concentrator in the system can increase the solar concentration. García-Fernández et al. [115] present an overview of the parabolic-trough collectors built and marketed over the last century, as well as the prototypes currently under development. Szargut and Stanek [116] dealt with the problem of optimizing the performance of a solar collector by correctly determining the collector area per unit of heat demand, the diameter of collector pipes and the distance of the pipe axes in the collector plate. Varun [117] implemented a GA for maximizing the thermal performance of flat plate solar air heaters by considering the different system and operating parameters. Chang and Ko [118] designed a hybrid heuristic method which combines PSO with nonlinear time-varying evolution in order to determine the tilt angle of photovoltaic modules with the aim of maximizing the electrical energy output of the modules. Zagrouba et al. [119] proposed a GA to identify the electrical parameters of photovoltaic solar cells and modules to determine the corresponding maximum power point from the illuminated current–voltage characteristic. Marston et al. [120] presented an optimization algorithm for designing linear concentrating solar collectors using stochastic programming and a Monte Carlo technique to quantify the performance of the collector design in terms of an objective function, which is then minimized using a modified Kiefer–Wolfowitz algorithm that uses sample size and step size controls.

An interesting problem related to photovoltaic systems is the optimal determination of their size. The sizing optimization of a stand-alone photovoltaic system is a complex optimization problem which aims to obtain acceptable energy and economic cost for the consumer, and a relatively correct energy supply quality. Mellit [121] analyzed the performance of artificial intelligence techniques for sizing stand-alone photovoltaic, grid-connected photovoltaic and photovoltaic-wind hybrid systems. Mellit et al. [122] applied ANN and GA for sizing photovoltaic systems. Yang et al. [123] proposed a sizing method to optimize the capacity sizes of different components of hybrid solar-wind power generation systems employing a battery bank. Li et al. [124] dealt with the sizing optimization problem of stand-alone photovoltaic power systems using hybrid energy storage technology. Thiaux et al. [125] applied NSGA-II to optimize stand-alone photovoltaic systems with the aim of quantifying the gross energy requirement reduction by minimizing the storage capacity. Kornelakis and Koutroulis [126] analyzed the optimization of photovoltaic grid-connected systems as follows: given a list of commercially available system devices, they select the optimal number and type and the optimal values of the photovoltaic module installation details, in such way that the total net economic benefit achieved during the system's operational lifetime period is maximized. Kornelakis and Marinakis [127] also applied PSO to this problem.

Cirre et al. [128] implemented two hierarchical approaches, fuzzy logic and physical model-based optimization, for control of a distributed solar collector field. The results obtained demonstrated that it is possible to automatically control the plant and exploit solar performance while remaining within operating constraints. Ammar et al. [129] applied a neuro-fuzzy algorithm for the daily optimum management of household photovoltaic panel generation without using storage equipment. The optimization of energy generation in a photovoltaic system is necessary to allow the photovoltaic cells to operate at the maximum power point corresponding to the maximum efficiency according to the irradiation and cell temperatures. Other authors have proposed an adaptive perturb and observe method that has fast dynamics and improved stability [130]. Water heating is often obtained with solar energy. In order to encourage wider application of centralized solar water heating systems for high-rise residential buildings, it is important to pursue an optimal design to achieve significant energy-saving potential. Fong et al. [131] implemented an EA for maximizing the energy saving of solar heating against conventional domestic electric heating. Kulkarni et al. [132] determined the water replenishment profile that optimizes the overall system using optimization methods.

### 3.3. Hydropower

Hydropower, hydraulic power or water power is power that is derived from the force or energy of moving water, which may be harnessed for useful purposes. Taking into account the fact that water is much denser than air, even a slow flowing stream of water, or moderate sea swell can yield considerable amounts of energy. There are several forms of water power currently in use or development. Broad categories include hydroelectricity, which is based on generating electrical power through the use of the gravitational force of falling or flowing water; and ocean energy, which mainly refers to the energy carried by ocean waves and tides.

In recent decades there has been increasing interest in the area of hydropower plant model development and its control [133]. The sizing of a small hydropower plant of the run-of-river type is very critical for the cost effectiveness of the investment. Anagnostopoulos and Papantonis [134] presented a stochastic EA for the optimal sizing of a small hydropower plant that simulates in detail the plant operation during the year with the aim of maximizing the economic benefit and the energy produced. Peña et al. [135] estimated the capacity of a mini-hydro plant based on time series forecasting. Yoo [136] tested a LP method for maximizing hydropower energy generation that also analyzes the effect and sensitivity of the model and reservoir storage on the maximization of hydropower energy generation based on calculations of optimal values. In the deregulated power market, the hydro producer has in principle no other objective than to produce electricity and sell with maximum and minimum market risk. Attention must focus on profit uncertainty caused by uncertainty in spot prices and reservoir inflow. Hongling et al. [137] presented a review of the state-of-the-art in hydropower operations considering profit risk under uncertainty and suggesting future directions for additional research and application. Ladurantaye et al. [138] analyzed deterministic and stochastic mathematical models for maximizing the profits obtained by selling electricity produced through a cascade of dams and reservoirs in a deregulated market. Numerical results based on historical data demonstrate the superiority of stochastic models over deterministic ones. Kuby et al. [139] presented a multi-objective combinatorial optimization method to analyze ecological-economic tradeoffs and to support complex decision-making associated with dam removal in a river system with the aim of minimizing loss of hydropower and maximizing storage capacity. Daily hydrothermal generation scheduling is an important problem that consists of determining the optimal amount of generated power for the hydro and thermal units of the system in the scheduling horizon of one day while satisfying the constraints of the hydroelectric system, thermal plants and electrical power system. This problem has been dealt with using heuristic optimization techniques, including a Modified Adaptive PSO algorithm [140]. Finardi et al. [141] solved the optimal scheduling of hydropower plants in a hydrothermal interconnected system by means of Lagrangian relaxation (LR) and sequential quadratic programming (SQP). Liu et al. [142] presented a stochastic LP framework for the hydropower portfolio management problem with uncertainty in market prices and inflows in the medium term. The results obtained showed that it is necessary to consider the uncertainty in inflows and market prices and incorporate the impact of uncertainties on the portfolio management problem. Pérez-Díaz et al. [143] applied a non-linear programming (NLP) scheduling model that determines both the optimal unit commitment (start-ups and shut-downs scheduling) and the generation dispatch of the committed units (hourly power output) for short-term operation scheduling of a hydropower plant. The results denote the good performance of this model which provides feasible and locally optimal operation schedules given by both the plant status (on/off) and the power to be generated in each hour of the day in order to maximize revenue. Khanmohammadi et al. [144] solved the unit commitment problem using NMS and PSO algorithms, while other approaches, such as stochastic programming have also been applied to this problem [145]. Lee [146] demonstrated the good performance of PSO to solve short-term hydroelectric generation scheduling of a power system with wind turbine generators in terms of computation efficiency and quality. The issue of load distribution among cascade hydropower stations is a dynamic optimization problem with multiple dimensions and multiple stages. Li et al. [147] applied an immune-based algorithm with PSO for optimizing load distribution among cascade hydropower stations, whose results show that it achieve a good load distribution with high convergence precision. Real-time hydropower reservoir operation is a continuous decision-making process that consists of determining the water level of a reservoir or the volume of water released from it. The hydropower operation is usually based on operating policies and rules defined and decided upon in strategic planning. Moeini et al. [148] proposed a fuzzy rule-based model for the operation of hydropower reservoirs whose rules are based on ideal or target storage levels. It is common practice in the hydropower industry to either shorten the maintenance duration or to postpone maintenance tasks in a hydropower system when there is expected unserved energy based on current water storage levels and forecast storage inflows. Foong et al. [149] tackled the problem of maintenance scheduling for these systems using a method that combines ACO and power plant maintenance scheduling.

Wave power, along with renewable energy-generating sources like tides and streams, has advantageous physical properties and predictability. Ocean waves represent a form of renewable energy created by wind currents passing over open water. Wave energy potential varies considerably in different parts of the world, and wave energy cannot be harnessed effectively everywhere. As commented above, the prediction of wind speed is a basic challenge for wind power generation. In the same manner, the prediction of water level is fundamental for ocean energy generation. Huang et al. [150] developed an ANN for water level predictions, with an application to coastal inlets taking into account long-term water level observations. Kazeminezhad et al. [151] analyzed an adaptive network-based fuzzy inference system and coastal engineering manual methods for predicting wave parameters. Reikard [152] evaluated the ability of time-series models to predict the energy from ocean waves by a hybrid model that combines ANN with time-varying regressions. Child and Venugopal [153] analyzed the influence of the spatial configuration of a wave energy device array upon total power output using two different approaches: the Parabolic Intersection method and a GA. The results obtained show that, although more computational effort is required, superior results may be obtained using GA compared to the Parabolic Intersection method. Ocean energy technologies for generating electricity include wave, tidal (barrages and turbines), and ocean thermal energy conversion systems [66]. Falcão [154] presented a stochastic optimization method for the energy conversion process from wave to air turbine, where the decision variable is the turbine size, represented by its rotor diameter, and the objectives to maximize are the electrical energy produced and the annual profit. Another interesting problem is that of the optimization of the shape of a wave energy collector to improve energy extraction, which is often solved with heuristic methods, such as GA [155]. Batten et al. [156] applied NMS for designing and optimizing energy output with tidal data for marine current turbines.

### 3.4. Bioenergy

Bioenergy is renewable energy made available from materials derived from biological sources. Biomass, a renewable energy source, is biological material from living, or recently living organisms, including plants and animals. Biomass is one of the most promising renewable energy sources, but more research is required to prove that power generation from biomass is both technically and economically viable. Biomass can be burned to produce steam for making electricity, or to provide heat to industries and homes. In addition biomass can be converted to other usable forms like methane gas, ethanol fuel and biodiesel fuel. Biomass power plants exist in over 50 countries around the world and supply a growing share of electricity. European countries are expanding their total share of power from biomass, such as Austria (7% of the renewable energy generation), Finland (20%), and Germany (5%) [66], while biogas for power generation is also a growing trend in many countries. Trends include growing use of solid biomass pellets, use of biomass in building-scale or community-scale combined heat and power plants, and use of biomass for centralized district heating systems [66]. The sustainability of electricity generation from biomass must be assessed according to the key indicators of price, efficiency, greenhouse gas emissions, availability, limitations, land use, water use and social impacts. Biomass produced electricity generally provides favorable price, efficiency, emissions, availability and limitations but often has unfavorably high land and water usage as well as social impacts [157]. Reche et al. [158] presented a binary PSO-based method to accomplish optimal location of biomass-fuelled systems for distributed power generation with forest residues as biomass source, and the results outperformed those obtained by a GA when maximizing a profitability index taking into account technical constraints. Rentizelas et al. [159] proposed an optimization method for multi-biomass energy conversion applications taking into account various technical, regulatory, social and logical constraints. PSO has also been applied for the optimal location and supply area for biomass-based power plants where the maximum electric power generated by the plant is considered as a constraint [160]. Vera et al. [161] applied a nature-inspired algorithm for the optimal location of a biomass power plant with the aim of providing the best profitability for investors.

With recent increases in oil prices, uncertainties concerning its availability and the need for clean and environment friendly fuels, there is renewed interest in vegetable oil fuels for diesel engines [162]. Biodiesel fuel can be made from new or used vegetable oils and animal fats, which are non-toxic, biodegradable, renewable resources. Sharma and Singh [163] presented a review addressing various aspects of biodiesel production. There is much discussion about the strengths and weaknesses of different biofuel support policies based on the experiences gained in pioneering countries and exploring scenarios for their possible impacts in the long-term [164]. Naik et al. [165] offer an interesting review of the first and second generations of biofuels from the sustainable point of view. Among this second generation of biofuels there are some promising alternatives, such as thermochemical conversion of biomass to biofuels. However, the complexity of the conversion process requires the modelling and optimization of the process integration methods to demonstrate an effective way for the exploitation of these interactions [166]. Alfonso et al. [167] developed a method to assess optimal management and energy use of distributed biomass resources, considering features such as biomass resources properties, plant size effect, available technologies for power, heat and solid biofuels generation, $CO_2$ emissions balance and quantification of potential biofuel consumers.

The use of biomass as a source of energy has been further enhanced in recent years and special attention has been paid to biomass gasification. Agugliaro [168] proposed the use of vegetable biomass from greenhouse residues to produce electrical energy by the gasification process. Due to the increasing interest in biomass gasification, some models that explain the design, simulation, optimization and process analysis of gasifiers have been presented, including gasification models based on thermodynamic equilibrium, kinetics and ANN [169]. Biogas, a byproduct of fermenting solid and liquid biomass, can be converted by a combustion engine to heat, power, and transport [66]. Madlener [170] performed a multi-criteria study with the aim of evaluating the performance of a large number of agricultural biogas plants in order to determine their relative performance in terms of economic, environmental, and social criteria and corresponding indicators.

### 3.5. Geothermal energy

Geothermal energy is the energy contained as heat inside the Earth. Geothermal heat pumps are a highly efficient, renewable energy technology for heating and cooling. This technology relies on the fact that, at depth, the Earth has a relatively constant temperature, warmer than the air in winter and cooler than the air in summer. The main advantage of using geothermal energy is that this renewable energy source can provide power 24 h a day due to it is constant, without intermittence problems compared to other renewable resources such as wind or solar energy. It is expensive to build a power station but operating costs are low, resulting in low energy costs for suitable sites. Geothermal power plants now exist in 19 countries, and new plants are commissioned annually, e.g. Indonesia, Italy, Turkey, and the United States in 2009 [66]. However, only a small fraction of the geothermal potential has been developed so far, and there is ample space for an accelerated use of geothermal energy both for electricity generation and direct applications. Geothermal energy, with its proven technology and abundant resources, can make a significant contribution towards reducing the emission of greenhouse gases [171]. Advantages of geothermal energy are especially visible in arid areas, where the establishment of human habitats strongly depends on the availability of fresh water. Further, geothermal resources are also used to heat greenhouses and to provide fresh water [172].

A geothermal heat pump can transfer heat stored in the Earth into a building during the winter, and transfer heat out of the building during the summer [173]. One of the most commonly used heating devices in geothermal systems is the heat exchanger, whose output conditions are based on several parameters. Among these parameters, the heat transfer area is one of the most important for heat exchangers. Dagdas [174] proposed an optimization method to solve this problem which provides maximum annual net profit. Tselepidou and Katsifarakis [175] presented a GA for the optimization of the exploitation system of a low enthalpy geothermal aquifer, with the aim of determining the annual pumping cost of the required flow and the amortization cost of the pipe network, which carries the hot water from the wells to a central water tank, situated on the border of the geothermal field. The results show that application of the proposed methodology allows better planning of low enthalpy geothermal heating systems.

### 3.6. Hybrid systems

The previous sections have presented the main problems related to different renewable energy sources. The discontinuity in the generation of most of the renewable energy sources often involves reliability problems associated with their operation. For instance, commercialized stand-alone street lighting systems based on the classical configuration coupling photovoltaic cells and battery cannot work all the year round in regions that are far from the equator [176]. Research and development efforts in solar, wind, and other renewable energy technologies must continue to improve their performance, establish techniques for accurately predicting their output and reliably integrate them with other conventional sources [177]. In the last decade, there has been a spectacular increase the interest in optimizing the design and control of stand-alone hybrid power generation systems in order to manage energy between the maximum energy captured and consumed energy [178]. If these hybrid systems are optimally designed, they can be more cost effective and reliable than single-renewable systems, and so there is increasing interest in determining the necessary conditions to install hybrid power plants systems due to their operational and economical advantages [179]. With the aim of optimizing the mix of the renewable system maximizing its contribution to the peak load, while minimizing the combined intermittence, at a minimum cost, some multi-objective algorithms have been proposed [180]. Katsigiannis et al. [181] presented a multi-objective algorithm which aims to minimize the energy cost of the system, while the total greenhouse gas emissions of the system during its lifetime are also minimized. Practical economic dispatch problems have non-linear, non-convex type objective function with intense equality and inequality constraints. The conventional optimization methods are not able to solve such problems due to local optimum solution convergence. Mahor et al. [182] applied PSO to solve this problem, and concluded that its performance was better than conventional optimization techniques. Brini et al. [183] solved the economic environmental dispatching of a hybrid power system including wind and solar thermal energies using a MOEA that simultaneously minimizes the fuel costs and the emission of polluting gases, while GA are also used for economic load dispatch optimization of power systems that include wind generation. Bernal-Agustín et al. [184] applied the well-known MOEA (SPEA) to the multi-objective design of isolated hybrid systems where the objectives to minimize are the total cost throughout the useful life of the installation and the pollutant emissions. The results obtained when designing a photovoltaic–wind–diesel system demonstrate the practical utility of the design method used. These authors later applied a MOEA to solve a three-objective version of this problem which, in addition to considering the useful life of the installation and the pollutant emissions, also considers, the unmet load in this hybrid system [185]. Ould [186] proposed a multi-objective GA for sizing a hybrid solar–wind-battery system with the aim of minimizing the annualized cost system and the loss of power supply probability. Bilal et al. [187] proposed a Pareto-based multi-objective GA for sizing a hybrid solar–wind-battery system with the aim of minimizing the annualized cost and minimizing the probability of loss of power supply. Montoya et al. [188] presented a hybrid Pareto-based multi-objective meta-heuristic that combined PAES with SA and TS to minimize voltage deviations and power losses in power networks, which can be extended to hybrid systems.

Hybrid renewable energy systems are becoming popular for remote area power generation applications due to advances in renewable energy technologies. With the aim of supervising this new kind of production system some papers discuss optimization techniques, including LP [189], fuzzy logic [190], etc. However, the design of hybrid systems is complex because of the uncertain renewable energy supplies, load demands and the non-linear characteristics of some components. Further, the overall evaluation of autonomous hybrid power systems that contain renewable and conventional power sources depends on economic and environmental criteria, which are often conflicting objectives. Therefore some authors have dealt with the problem of determining the optimal combination of renewable energy technologies taking into account not only the renewable energy resources, but also the technology characterization, incentives and economic parameters (installed cost, maintenance costs, etc.). Lee and Chen [2] proposed a PSO algorithm to solve the wind-photovoltaic capacity coordination for a time-of-use rate industrial user with the aim of maximizing the economic benefits of investing in a wind generation system and a photovoltaic generation system. Kaviani et al. [191] optimized a hybrid wind-photovoltaic-fuel cell generation system with a PSO with the aim of minimizing the annual cost of the hybrid system subject to reliable supply for the demand. Lagorse et al. [176] applied the GA and the simplex algorithm for optimizing a hybrid system coupling a photovoltaic, a battery and a fuel cell for stand-alone street lighting systems. Eke et al. [192] presented an optimization method for designing a wind-photovoltaic hybrid system to cover the electricity consumption taking into account the monthly average solar irradiation and wind speed data. Giannakoudis et al. [193] proposed an optimization method for the design and operation of a hybrid power generation system that consists of photovoltaic panels, wind generators, accumulators, an electrolysis apparatus, hydrogen storage tanks, a compressor, a fuel cell and a diesel generator.

Isolated electrical power generating units can be used as an economically viable alternative to electrify remote villages where grid extension is not feasible. One of the options for building isolated power systems is by hybridizing renewable power sources like wind, solar, micro-hydro, etc. along with energy storage systems [194]. Bernal-Agustín and Dufo-López [195] analyzed the main research strategies on optimization of hybrid systems with battery energy storage. Zhou et al. [4] presented a review of the current state of the art in the simulation, optimization and control technologies for the stand-alone hybrid solar-wind energy systems with battery storage, which concludes that there is a large variety of techniques for accurately predicting their output and reliably integrating them with other renewable or conventional power generation sources. Other authors have applied GA for the optimal configuration of power system on islands installing a renewable energy power production plant consisting of diesel generators, wind turbine generators, photovoltaic system and batteries [196]. Balamurugan et al. [197] proposed a hybrid energy system consisting of biomass, wind, solar photovoltaic and battery to deliver energy at optimum efficiency, maintaining a fair level of energy storage to meet the peak load demand during low or no solar radiation periods or during low wind periods. Nema et al. [198] reviewed the current state of the design, operation and control requirements of the stand-alone photovoltaic solar–wind hybrid energy systems with conventional backup source, diesel or grid, and highlighted the future developments.

When designing a hybrid system both the sizing of the elements and the control strategy must be correctly analyzed [199]. García and Weisser [200] applied LP and fixed dispatch to determine the size of grid units and dispatch in a wind-diesel power system with hydrogen storage with the aim of minimizing cost taking as data one-year time series of hourly wind speed and electricity demand. Koutroulis et al. [201] proposed a GA for optimal sizing of stand-alone photovoltaic-wind generator systems, which selects the optimal number and type of units to minimize the cost subject to the constraint that the load energy requirements are completely covered. Yang et al. [202] presented a GA for optimal sizing to optimize the configurations of a hybrid solar–wind system employing battery banks, where the decision variables are the number of photovoltaic modules, wind turbines and batteries, the photovoltaic module slope angle and wind turbine installation height. Del Real et al. [203] presented a procedure to evaluate the optimal element sizing of a hybrid power system that incorporates a wind generator, batteries and intermediate hydrogen storage according to real wind data and averaged residential demands. Bernal-Agustın and Dufo-López [204] presented an EA for the efficient design and control of a hybrid system of electrical energy generation that consists of a complex photovoltaic–wind–diesel–batteries–hydrogen system. The results obtained show that the EA was able to obtain good solutions with low computational effort. Zervas et al. [205] studied a hybrid power generation system consisting of a photovoltaic array, electrolyser, metal hydride tanks, and proton exchange membrane fuel cells, which has advantages compared to stand-alone photovoltaic systems, but the optimization of its operation is a rather complicated task. Diaf et al. [206] analyzed how to estimate the appropriate dimensions of a stand-alone hybrid photovoltaic-wind system that guarantees the energy autonomy of a typical remote consumer with the lowest levelized cost of energy. Hakimi and Moghaddas-Tafreshi [207] demonstrated that PSO is able to minimize the total costs of a hybrid power system formed by fuel cells, wind units, electrolysers, a reformer, anaerobic reactor and hydrogen tanks and which uses biomass as an available energy resource, such that the demand is met. The same authors also applied PSO to the problem of sizing in a hybrid power system such that the total costs of the system is minimized and the demand of residential area is met [207]. Another interesting problem is the impact of renewable energy on power system operation. In particular, there exist several studies about hybrid power systems where electrical networks include renewable energy sources. Razak et al. [208] presented an optimization method for minimizing the excess energy and cost of energy in a hybrid renewable system that combines pico hydro turbines, wind turbines, solar photovoltaic panels and diesel generator, and results showed that it is important to consider the amount of excess energy the system produces in order to reduce the energy cost. The planning algorithm accounts for the uncertainty of wind power forecasts and power market price uncertainty. Chakraborty et al. [209] implemented GA and PSO for solving a planning problem for thermal units integrated with wind and solar energy systems. Matevosyan et al. [210] proposed a day-ahead planning algorithm for a multi-reservoir hydropower system coordinated with wind power and sharing the same transmission lines, though hydropower has priority for transmission capacity. Castronuovo and Lopes [211] proposed an optimization algorithm to identify the optimum daily operational strategy to be followed by wind turbines and hydro generation pumping equipment. Jurado and Saenz [212] presented a neuro-fuzzy controller for a wind–diesel system composed of a stall regulated wind turbine with an induction generator connected to an ac bus-bar in parallel with a diesel generator set having a synchronous generator. The authors show that this approach achieves better results than fixed-parameter fuzzy logic controllers and PID controllers. Dufo-López and Bernal-Agustín [213] implemented a GA for the design and control of a hybrid photovoltaic-diesel hybrid system. The hybrid wind-hydro power generation is an attractive solution for isolated, autonomous electric grids in order to increase the wind energy penetration and cost-effectiveness. Anagnostopoulos and Papantonis [214] combined an evaluation algorithm that simulates in detail the plant operation and an automated optimization software based on EA for optimum sizing of the various components of a reversible hydraulic system, i.e. turbine size, the size and the number of the pumps, the penstock diameter and thickness, the capacity of the reservoirs and some financial parameters. Anarbaev et al. [215] modelled a double-loop solar plus fuel boiler installation scheme that increases the hot water load replacement factor thanks to the heat produced by the solar technical part with increase of the thermal efficiency of the solar attachment.

## 4. Conclusions

This paper provides an overview of the latest research developments concerning to the use of optimization algorithms for design, planning and control problems in the field of renewable and sustainable energy. The review of over two hundred papers from the major referenced journals in the fields of renewable energy and computational optimization offers interesting conclusions that can be useful for renewable energy researchers. The first conclusion of this review is that the number of research papers that use optimization methods to solve renewable energy problems has increased dramatically in recent years, especially for wind and solar energy systems. Some of these optimization methods are based on traditional approaches, such as mixed-integer and interval linear-programming, Lagrangian relaxation, quadratic programming, and Nelder–Mead Simplex search, while a growing number of research papers tackle these problems using heuristic optimization methods, especially genetic algorithms and particle swarm optimization. On the other hand, some researchers have solved multi-objective problems related to renewable energy systems using Pareto-optimization techniques. However, parallel processing has not been sufficiently explored for solving these problems.

Therefore, it can be concluded that the use of heuristic approaches, Pareto-based multi-objective optimization and parallel processing are promising research areas in the field of renewable and sustainable energy.

## Acknowledgements

This work has been supported by grant P2007-TIC-02988 (CICE, Junta de Andalucia).

## References

[1] Vine E. Breaking down the silos: the integration of energy efficiency, renewable energy, demand response and climate change. Energy Efficiency 2008;1:49–63.
[2] Lee T-Y, Chen C-L. Wind-photovoltaic capacity coordination for a time-of-use rate industrial user. IE Transactions on Renewable Power Generation 2009;3(2):152–67.
[3] Martiskainen M, Coburn J. The role of information and communication technologies (ICTs) in household energy consumption/prospects for the UK. Energy Efficiency 2010, doi:10.1007/s12053-010-9094-2.
[4] 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. Applied Energy 2010;87(2):380–9.
[5] Strupczewskim A. Accident risks in nuclear-power plants. Applied Energy 2003;75(1–2):79–86.
[6] Skoglund A, Leijon M, Rehn A, Lindahl M, Waters R. On the physics of power, energy and economics of renewable electric energy sources-Part II. Renewable Energy 2010;35(8):1735–40.
[7] Evans A, Strezov V, Evans TJ. Assessment of sustainability indicators for renewable energy technologies. Renewable and Sustainable Energy Reviews 2009;13(5):1082–8.
[8] Lund H. Renewable energy strategies for sustainable development. Energy 2007;32(6):912–9.
[9] Hepbasli A. A key review on exergetic analysis and assessment of renewable energy resources for a sustainable future. Renewable and Sustainable Energy Reviews 2008;12(3):593–661.
[10] Varun, Prakash R, Bhat IK. Energy, economics and environmental impacts of renewable energy systems. Renewable and Sustainable Energy Reviews 2009;13(9):2716–21.
[11] Jebaraj S, Iniyan S. A review of energy models. Renewable and Sustainable Energy Reviews 2006;10(4):281–311.
[12] Pardalos PM, Resende MGC. Handbook of applied optimization. Oxford University Press; 2002.
[13] Du D-H, Pardalos PM. Handbook of combinatorial optimization: supplement volume B. Springer; 2005.
[14] Garey MR, Johnson DS. Computers and intractability: a guide to the theory of NP-completeness. San Francisco: W.H. Freeman and Company; 1979.
[15] Gendreau M, Potvin J-Y. Handbook of metaheuristics. International series in operations research and management science. Springer; 2010.
[16] Alba E. Parallel metaheuristics: a new class of algorithms. Wiley and Sons; 2005.
[17] Glover F, Kochenberger GA. Handbook of meta-heuristics. International series in operations research management science, vol. 57. Springer; 2003.
[18] Hajela P, Y-Lin C. Genetic search strategies in multi-criterion optimal design. Structural Optimization 1992;4:99–107.
[19] Goldberg DE. Genetic algorithms in search optimization and machine learning. Addison-Wesley; 1989.
[20] Baños R, Gil C, Paechter B, Ortega J. A hybrid meta-heuristic for multi-objective optimization: MOSATS. Journal of Mathematical Modelling and Algorithms 2007;6(2):213–30.
[21] Ehrgott M, Gandibleux X. Hybrid metaheuristics for multi-objective combinatorial optimization. Hybrid Metaheuristics: Studies in Computational Intelligence 2008;114:221–59.
[22] Ma T, Nakamori Y. Modeling technological change in energy systems—from optimization to agent-based modeling. Energy 2009;34/7:873–9.
[23] Cai YP, Huang GH, Yang ZF, Lin QG, Tan Q. Community-scale renewable energy systems planning under uncertainty—an interval chance-constrained programming approach. Renewable and Sustainable Energy Reviews 2009;13(4):721–35.
[24] Soroudi A, Ehsan M, Zareipour H. A practical eco-environmental distribution network planning model including fuel cells and non-renewable distributed energy resources. Renewable Energy 2011;36(1):179–88.
[25] Kahraman C, Kaya I, Cebi S. A comparative analysis for multiattribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process. Energy 2009;34:1603–16.
[26] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Applied Energy 2010;87(4):1059–82.
[27] Sadegheih A. A novel formulation of carbon emissions costs for optimal design configuration of system transmission planning. Renewable Energy 2010;35(5):1091–7.
[28] Sadegheih A. Optimal design methodologies under the carbon emission trading program using MIP, GA, SA, and TS. Renewable and Sustainable Energy Reviews 2010, doi:10.1016/j.rser.2010.07.035.
[29] Zangeneh A, Jadid S, Rahimi-Kian A. Promotion strategy of clean technologies in distributed generation expansion planning. Renewable Energy 2009;34(12):2765–73.
[30] Cai YP, Huang GH, Tan Q, Yang ZF. Planning of community-scale renewable energy management systems in a mixed stochastic and fuzzy environment. Renewable Energy 2009;34(7):1833–47.
[31] Kowalski K, Stagl S, Madlener R, Omann I. Sustainable energy futures: methodological challenges in combining scenarios and participatory multi-criteria analysis. European Journal of Operational Research 2009;197(3):1063–74.
[32] AlRashidi MR, EL-Naggar KM. Long term electric load forecasting based on particle swarm optimization. Applied Energy 2010;87(1):320–6.
[33] Dicorato M, Forte G, Trovato M. Environmental-constrained energy planning using energy-efficiency and distributed-generation facilities. Renewable Energy 2008;33(6):1297–313.
[34] Ahadi-Oskui T, Alperin H, Nowak I, Cziesla F, Tsatsaronis G. A relaxation-based heuristic for the design of cost-effective energy conversion systems. Energy 2006;31(10–11):1346–57.
[35] Fleten S-E, Maribu KM, Wangensteen I. Optimal investment strategies in decentralized renewable power generation under uncertainty. Energy 2007;32(5):803–15.
[36] Hiremath RB, Shikha S, Ravindranath NH. Decentralized energy planning; modeling and application—a review. Renewable and Sustainable Energy Reviews 2007;11(5):729–52.
[37] Yokoyama R, Wakui T, Satake R. Prediction of energy demands using neural network with model identification by global optimization. Energy Conversion and Management 2009;50:319–27.
[38] Mitchell K, Nagrial M, Rizk J. Simulation and optimization of renewable energy systems. International Journal of Electrical Power and Energy Systems 2005;27(3):177–88.
[39] Alvarez-Valdes R, Crespo E, Tamarit JM, Villa F. GRASP and path relinking for project scheduling under partially renewable resources. European Journal of Operational Research 2008;189(3):1153–70.
[40] Pohekar SD, Ramachandran M. Application of multi-criteria decision making to sustainable energy planning—a review. Renewable and Sustainable Energy Reviews 2004;8(4):365–81.
[41] Løken E. Use of multicriteria decision analysis methods for energy planning problems. Renewable and Sustainable Energy Reviews 2007;11(7):1584–95.
[42] Wang J-J, Jing Y-Y, Zhang C-F, Zhao J-H. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews 2009;13(9):2263–78.
[43] Alarcón-Rodríguez A, Ault G, Galloway S. Multi-objective planning of distributed energy resources: A review of the state-of-the-art. Renewable and Sustainable Energy Reviews 2010;14:1353–66.
[44] Franco A, Salza P. Strategies for optimal penetration of intermittent renewables in complex energy systems based on techno-operational objectives. Renewable Energy 2011;36(2):743–53.
[45] Sood YR, Singh R. Optimal model of congestion management in deregulated environment of power sector with promotion of renewable energy sources. Renewable Energy 2010;35(8):1828–36.
[46] Niknam T, Firouzi BB. A practical algorithm for distribution state estimation including renewable energy sources. Renewable Energy 2009;34:2309–16.
[47] Ostergaard PA. Reviewing optimization criteria for energy systems analyses of renewable energy integration. Energy 2009;34:1236–45.
[48] Niknam T, Meymand HZ, Nayeripour M. A practical algorithm for optimal operation management of distribution network including fuel cell power plants. Renewable Energy 2010;35(8):1696–714.
[49] Yongping Y, Rongrong Z, Liqiang D, Masek O, Oakey J. Study on multi-objective optimization of load dispatch including renewable energy and CCS technologies. International Journal of Energy Research 2010;34:702–15.
[50] Löhndorf N, Minner S. Optimal day-ahead trading and storage of renewable energies-an approximate dynamic programming approach. Energy Systems 2010;1(1):61–77.
[51] Reca J, Martínez J, Baños R, Gil C. Optimal design of gravity-fed looped water distribution networks considering the resilience index. ASCE Journal of Water Resources Planning and Management 2008;134(3):234–8.
[52] Reca J, Martínez J, Gil C, Baños R. Application of several meta-heuristic techniques to the optimization of real looped water distribution networks. Water Resources Management 2008;22(10):1367–79.
[53] Baños R, Gil C, Reca J, Martínez J. Scatter search for multi-objective optimization: a comparative study. Computational Optimization and Applications 2009;42(3):421–41.
[54] Baños R, Gil C, Reca J, Ortega J. A Pareto-based memetic algorithm for optimization of looped water distribution systems. Engineering Optimization 2010;42(3):223–40.
[55] Kumar A, Kandpal TC. Renewable energy technologies for irrigation water pumping in India: a preliminary attempt towards potential estimation. Energy 2007;32(5):861–70.
[56] Badran O. Wind turbine utilization for water pumping in Jordan. Journal of Wind Engineering and Industrial Aerodynamics 2003;91(10):1203–14.
[57] Vieira F, Ramos HM. Optimization of operational planning for wind/hydro hybrid water supply systems. Renewable Energy 2009;34(3):928–36.

[58] Chinese D, Meneghetti A, Nardin G. Waste-to-energy based greenhouse heating: exploring viability conditions through optimization models. Renewable Energy 2005;30(10):1573–86.
[59] Hernández-Escobedo Q, Manzano-Agugliaro F, Gazquez-Parra JA, Zapata-Sierra A. Is the wind a periodical phenomenon? The case of Mexico. Renewable and Sustainable Energy Reviews 2011;15:721–8.
[60] Thor S-E, Weis-Taylor P. Long-term research and development needs for wind energy for the time frame 2000–2020. Wind Energy 2002;5:73–5.
[61] Hernández-Escobedo Q, Manzano-Agugliaro F, Zapata-Sierra A. The wind power of Mexico. Renewable and Sustainable Energy Reviews 2010;14:2830–40.
[62] Henriksen LC. Wind energy literature survey no 16. Wind Energy 2010;13:524–6.
[63] Nigim KA, Parker P. Heuristic and probabilistic wind power availability estimation procedures: improved tools for technology and site selection. Renewable Energy 2007;32(4):638–48.
[64] Li YF, Li YP, Huang GH, Chen X. Energy and environmental systems planning under uncertainty—an inexact fuzzy-stochastic programming approach. Applied Energy 2010;87(10):3189–211.
[65] Zhao M, Chen Z, Blaabjerg F. Optimization of electrical system for offshore wind farms via genetic algorithm. IE Transactions on Renewable Power Generation 2009;3(2):205–16.
[66] Renewables 2010. Global status report. Deutsche Gesellschaft für Technische Zusammenarbeit (GTZ) GmbH.
[67] Benini E, Toffolo A. Optimal design of horizontal-axis wind turbines using blade-element theory and evolutionary computation. Journal of Solar Energy Engineering 2002;124(4):357–63.
[68] Maalawi KY, Negm HM. Optimal frequency design of wind turbine blades. Journal of Wind Engineering and Industrial Aerodynamics 2002;90(8):961–86.
[69] Sareni B, Abdelli A, Roboam X, Tran DH. Model simplification and optimization of a passive wind turbine generator. Renewable Energy 2009;34(12):2640–50.
[70] Lund E, Stegmann J. On structural optimization of composite shell structures using a discrete constitutive parametrization. Wind Energy 2005;8:109–24.
[71] Svanberg K. The method of moving asymptotes-a new method for structural optimization. International Journal for Numerical Methods in Engineering 1987;24:359–73.
[72] Jensen FM, Puri AS, Dear JP, Branner J, Morris A. Investigating the impact of non-linear geometrical effects on wind turbine blades—Part 1: current status of design and test methods and future challenges in design optimization. Wind Energy 2010, doi:10.1002/we.415.
[73] Li H, Chen Z, Polinder H. Optimization of multibrid permanent-magnet wind generator systems. IEEE Transactions on Energy Conversion 2009;24(1):82–92.
[74] Kusiak A, Zhang Z, Li M. Optimization of wind turbine performance with data-driven models. IEEE Transactions on Sustainable Energy 2010;1(2):62–76.
[75] Roy A, Kedare SB, Bandyopadhyay S. Application of design space methodology for optimum sizing of wind-battery systems. Applied Energy 2009;86(12):2690–703.
[76] Xudong W, Shen WZ, Zhu WJ, Sørensen JN, Jin C. Shape optimization of wind turbine blades. Wind Energy 2009;12:781–803.
[77] Fuglsang P, Thomsen K. Site-specific design optimization of 1.5–2.0 MW wind turbines. Journal of Solar Energy Engineering 2001;123(4):296–303.
[78] Fuglsang P, Bak C, Schepers JG, Bulder B, Cockerill TT, Claiden P, et al. Site-specific design optimization of wind turbines. Wind Energy 2002;5:261–79.
[79] Kusiak A, Zheng H. Optimization of wind turbine energy and power factor with an evolutionary computation algorithm. Energy 2010;35:1324–32.
[80] Kusiak A, Zheng H, Song Z. Power optimization of wind turbines with data mining and evolutionary computation. Renewable Energy 2010;35:695–702.
[81] Kongnam C, Nuchprayoon S, Premrudeepreechacharn S, Uatrongjit S. Decision analysis on generation capacity of a wind park. Renewable and Sustainable Energy Reviews 2009;13(8):2126–33.
[82] Hameed Z, Hong YS, Cho YM, Ahn SH, Song CK. Condition monitoring and fault detection of wind turbines and related algorithms: a review. Renewable and Sustainable Energy Reviews 2009;13(1):1–39.
[83] Üstüntaş T, Şahin A. Wind turbine power curve estimation based on cluster center fuzzy logic modeling. Journal of Wind Engineering and Industrial Aerodynamics 2008;96(5):611–20.
[84] Shimizu E, Isogai K, Obayashi S. Multiobjective design study of a flapping wing power generator. Journal of Fluids Engineering 2008;130(2):021104–11.
[85] Rašuo BP, Bengin AC. Optimization of wind farm layout. FME Transactions 2010;38:107–14.
[86] Grady SA, Hussaini MY, Abdullah MM. Placement of wind turbines using genetic algorithms. Renewable Energy 2005;30(12):259–70.
[87] Emami A, Noghreh P. New approach on optimization in placement of wind turbines within wind farm by genetic algorithms. Renewable Energy 2010;35(7):1559–64.
[88] Serrano J, Gonzalez AG, Castro J, Riquelme J, Burgos M. Optimization of wind farm turbines layout using an evolutive algorithm. Renewable Energy 2010;35:1671–81.
[89] Kusiak A, Song Z. Design of wind farm layout for maximum wind energy capture. Renewable Energy 2010;35(3):685–94.
[90] Herbert GMJ, Iniyan S, Goic R. Performance, reliability and failure analysis of wind farm in a developing country. Renewable Energy 2010;35(12):2739–51.
[91] Mustakerov I, Borissova D. Wind turbines type and number choice using combinatorial optimization. Renewable Energy 2010;35(9):1887–94.
[92] Dukpa A, Duggal I, Venkatesh B, Chang L. Optimal participation and risk mitigation of wind generators in an electricity market. IE Transactions on Renewable Power Generation 2010;4(2):165–75.
[93] Kusiak A, Li W. Estimation of wind speed: a data-driven approach. Journal of Wind Engineering and Industrial Aerodynamics 2010;98(10–11):559–67.
[94] Abdel-Aal RE, Elhadidy MA, Shaahid SM. Modeling and forecasting the mean hourly wind speed time series using GMDH-based abductive networks. Renewable Energy 2009;34(7):1686–99.
[95] Pinson P, Christensen LEA, Madsen H, Sørensen PE, Donovan MH, Jensen LE. Regime-switching modelling of the fluctuations of offshore wind generation. Journal of Wind Engineering and Industrial Aerodynamics 2008;96(12):2327–47.
[96] Zhang L, Wirth A. Wind energy management with battery storage. Journal of the Operational Research Society 2010;61:1510–22.
[97] Boqiang R, Chuanwen J. A review on the economic dispatch and risk management considering wind power in the power market. Renewable and Sustainable Energy Reviews 2009;13(8):2169–74.
[98] Kongnam C, Nuchprayoon S. A particle swarm optimization for wind energy control problem. Renewable Energy 2010;35(11):2431–8.
[99] Kuo C-C. Wind energy dispatch considering environmental and economic factors. Renewable Energy 2010;35(10):2217–27.
[100] Ko H, Jatskevich J. Power quality control of wind-hybrid power generation system using fuzzy-LQR controller. IEEE Transactions on Energy Conversion 2007;22(2):516–27.
[101] Kusiak A, Li W, Song Z. Dynamic control of wind turbines. Renewable Energy 2010;35(2):456–63.
[102] Li QS, Liu DK, Fang JQ, Tam CM. Multi-level optimal design of buildings with active control under winds using genetic algorithms. Journal of Wind Engineering and Industrial Aerodynamics 2000;86(1):65–86.
[103] Charron R, Athienitis AK. Design and optimization of net-zero energy solar homes. ASHRAE Transactions 2006;112(2):285–95.
[104] Kilkis BI. An exergy aware optimization and control algorithm for sustainable building. International Journal of Green Energy 2004;1(1):65–77.
[105] Diakaki C, Grigoroudis E, Kabelis N, Kolokotsa D, Kalaitzakis K, Stavrakakis G. A multi-objective decision model for the improvement of energy efficiency in buildings. Energy 2010, doi:10.1016/j.energy.2010.05.012.
[106] Bosch JL, López G, Batlles FJ. Daily solar irradiation estimation over a mountainous area using artificial neural networks. Renewable Energy 2008;33(7):1622–8.
[107] Cao J, Lin X. Application of the diagonal recurrent wavelet neural network to solar irradiation forecast assisted with fuzzy technique. Engineering Applications of Artificial Intelligence 2008;21:1255–63.
[108] Zervas PL, Sarimveis H, Palyvos JA, Markatos NCG. Prediction of daily global solar irradiance on horizontal surfaces based on neural-network techniques. Renewable Energy 2008;33(8):1796–803.
[109] Mellit A, Kalogirou SA, Shaari S, Salhi H, Arab AH. Methodology for predicting sequences of mean monthly clearness index and daily solar radiation data in remote areas: Application for sizing a stand-alone PV system. Renewable Energy 2008;33(7):1570–90.
[110] Paul D, Mandal SN, Mukherjee D, Chaudhuri SRB. Optimization of significant insolation distribution parameters—a new approach towards BIPV system design. Renewable Energy 2010;35(10):2182–91.
[111] Kenisarin M, Mahkamov K. Solar energy storage using phase change materials. Renewable and Sustainable Energy Reviews 2007;11(9): 1913–65.
[112] Kalogirou SA. Optimization of solar systems using artificial neural-networks and genetic algorithms. Applied Energy 2004;77(4):383–405.
[113] Aronova ES, Grilikhes VA, Shvarts MZ. Optimization of arrangement of photoelectric power plants with radiation concentrators in solar electric power plant design. Applied Solar Energy 2008;44/4:237–42.
[114] Klychev SI, Zakhidov RA, Bakhramov SA, Dudko YA, Khudoikulov AY. Parameter optimization for paraboloid-cylinder-receiver system of thermal power plants. Applied Solar Energy 2009;45(4):281–4.
[115] García-Fernández A, Zarza E, Valenzuela L, Pérez M. Parabolic-trough solar collectors and their applications. Renewable and Sustainable Energy Reviews 2010;14(7):1695–721.
[116] Szargut J, Stanek W. Thermo-ecological optimization of a solar collector. Energy 2007;32(4):584–90.
[117] Varun S. Thermal performance optimization of a flat plate solar air heater using genetic algorithm. Applied Energy 2010;87(5):1793–9.
[118] Chang Y-P, Ko C-N. A PSO method with nonlinear time-varying evolution based on neural network for design of optimal harmonic filters. Expert Systems with Applications: An International Journal 2009;36(3): 6809–16.
[119] Zagrouba M, Sellami A, Bouaïcha M, Ksouri M. Identification of PV solar cells and modules parameters using the genetic algorithms: application to maximum power extraction. Solar Energy 2010;84(5):860–6.
[120] Marston AJ, Daun KJ, Collins MR. Geometric optimization of concentrating solar collectors using Monte Carlo simulation. Journal of Solar Energy Engineering 2010;132(4):041002.
[121] Mellit A, Kalogirou SA, Hontoria L, Shaari S. Artificial intelligence techniques for sizing photovoltaic systems: a review. Renewable and Sustainable Energy Reviews 2009;13(2):406–19.

[122] Mellit A, Kalogirou SA, Drif M. Application of neural networks and genetic algorithms for sizing of photovoltaic systems. Renewable Energy 2010;35(12):2881–93.
[123] Yang H, Lu L, Zhou W. A novel optimization sizing model for hybrid solar-wind power generation system. Solar Energy 2007;81:76–84.
[124] Li C-H, Zhu X-J, Cao G-Y, Sui S, Hu M-R. Dynamic modeling and sizing optimization of stand-alone photovoltaic power systems using hybrid energy storage technology. Renewable Energy 2009;34(3):815–26.
[125] Thiaux Y, Seigneurbieux J, Multon B, Ahmed HB. Load profile impact on the gross energy requirement of stand-alone photovoltaic systems. Renewable Energy 2010;35(3):602–13.
[126] Kornelakis A, Koutroulis E. Methodology for the design optimization and the economic analysis of grid-connected photovoltaic. IE Transactions on Renewable Power Generation 2009;3(4):476–92.
[127] Kornelakis A, Marinakis Y. Contribution for optimal sizing of grid-connected PV-systems using PSO. Renewable Energy 2010;35(6):1333–41.
[128] Cirre CM, Berenguel M, Valenzuela L, Klempous R. Reference governor optimization and control of a distributed solar collector field. European Journal of Operational Research 2009;193:709–17.
[129] Ammar MB, Chaabene M, Elhajjaji A. Daily energy planning of a household photovoltaic panel. Applied Energy 2010;87(7):2340–51.
[130] Piegari L, Rizzo R. Adaptive perturb and observe algorithm for photovoltaic maximum power point tracking. IE Transactions on Renewable Power Generation 2010;4(4):317–32.
[131] Fong KF, Chow TT, Hanby VI. Development of optimal design of solar water heating system by using evolutionary algorithm. Journal of Solar Energy Engineering 2007;129(4):499–501.
[132] Kulkarni GN, Kedare SB, Bandyopadhyay S. Optimization of solar water heating systems through water replenishment. Energy Conversion and Management 2009;50(3):837–46.
[133] Kishor N, Saini RP, Singh SP. A review on hydropower plant models and control. Renewable and Sustainable Energy Reviews 2007;11:776–96.
[134] Anagnostopoulos JS, Papantonis DE. Optimal sizing of a run-of-river small hydropower plant. Energy Conversion and Management 2007;48(10):2663–70.
[135] Peña R, Medina A, Anaya-Lara O, McDonald JR. Capacity estimation of a minihydro plant based on time series forecasting. Renewable Energy 2009;34(5):1204–9.
[136] Yoo JH. Maximization of hydropower generation through the application of a linear programming model. Journal of Hydrology 2009;376(1–2):182–7.
[137] Hongling L, Chuanwen J, Yan Z. A review on risk-constrained hydropower scheduling in deregulated power market. Renewable and Sustainable Energy Reviews 2008;12(5):1465–75.
[138] Ladurantaye DD, Gendreau M, Potvin J-Y. Optimizing profits from hydroelectricity production. Computers and Operations Research 2009;36(2):499–529.
[139] Kuby MJ, Fagan WF, ReVelle CS, Graf WL. A multiobjective optimization model for dam removal: An example trading off salmon passage with hydropower and water storage in the Willamette basin. Advances in Water Resources 2005;28(8):845–55.
[140] Amjady N, Soleymanpour HR. Daily hydrothermal generation scheduling by a new modified adaptive particle wwarm optimization technique. Electric Power Systems Research 2010;80:723–32.
[141] Finardi EC, Da Silva EL, Sagastizabal C. Solving the unit commitment problem of hydropower plants via Lagrangian relaxation and sequential quadratic programming. Computational and Applied Mathematics 2005;24(3):317–41.
[142] Liu H, Jiang C, Zhang Y. Portfolio management of hydropower producer via stochastic programming. Energy Conversion and Management 2009;50:2593–9.
[143] Pérez-Díaz JI, Wilhelmi JR, Sánchez-Fernández JA. Short-term operation scheduling of a hydropower plant in the day-ahead electricity market. Electric Power Systems Research 2010;80(12):1535–42.
[144] Khanmohammadi S, Amiri M, Haque MT. A new three-stage method for solving unit commitment problem. Energy 2010;35(7):3072–80.
[145] Fleten SE, Kristoffersen TK. Short-term hydropower production planning by stochastic programming. Computers and Operations Research 2008;35:2656–71.
[146] Lee TY. Short term hydroelectric power system scheduling with wind turbine generators using the multi-pass iteration particle swarm optimization approach. Energy Conversion and Management 2008;49(4):751–60.
[147] Li A, Wang L, Li J, Ji C. Application of immune algorithm-based particle swarm optimization for optimized load distribution among cascade hydropower stations. Computers and Mathematics with Applications 2009;57:1785–91.
[148] Moeini R, Afshar A, Afshar MH. Fuzzy rule-based model for hydropower reservoirs operation. International Journal of Electrical Power and Energy Systems 2010, doi:10.1016/j.ijepes.2010.08.012.
[149] Foong WK, Maier HR, Simpson AR. Power plant maintenance scheduling using ant colony optimization: an improved formulation. Engineering Optimization 2008;40(4):309–29.
[150] Huang W, Murray C, Kraus N, Rosati J. Development of a regional neural network for coastal water level predictions. Ocean Engineering 2003;30(17):2275–95.
[151] Kazeminezhad MH, Etemad-Shahidi A, Mousavi SJ. Application of fuzzy inference system in the prediction of wave parameters. Ocean Engineering 2005;32(14–15):1709–25.
[152] Reikard G. Forecasting ocean wave energy: tests of time-series models. Ocean Engineering 2009;36(5):348–56.
[153] Child BFM, Venugopal V. Optimal configurations of wave energy device arrays. Ocean Engineering 2010;37(16):1402–17.
[154] Falcão AFO. Stochastic modelling in wave power-equipment optimization: maximum energy production versus maximum profit. Ocean Engineering 2004;31(11–12):1407–21.
[155] McCabe AP, Aggidis GA, Widden MB. Optimizing the shape of a surge-and-pitch wave energy collector using a genetic algorithm. Renewable Energy 2010;35(12):2767–75.
[156] Batten WMJ, Bahaj AS, Molland AF, Chaplin JR. Experimentally validated numerical method for the hydrodynamic design of horizontal axis tidal turbines. Ocean Engineering 2007;34:1013–20.
[157] Evans A, Strezov V, Evans TJ. Sustainability considerations for electricity generation from biomass. Renewable and Sustainable Energy Reviews 2010;14(5):1419–27.
[158] Reche P, Jurado F, Ruiz N, García S, Gómez M. Particle swarm optimization for biomass-fuelled systems with technical constraints. Engineering Applications of Artificial Intelligence 2008;21(8):1389–96.
[159] Rentizelas AA, Tatsiopoulos IP, Tolis A. An optimization model for multi-biomass tri-generation energy supply. Biomass and Bioenergy 2009;33(2):223–33.
[160] Reche P, García S, Ruiz N, Jurado F. A method for particle swarm optimization and its application in location of biomass power plants. International Journal of Green Energy 2008;5(3):199–211.
[161] Vera D, Carabias J, Jurado F, Ruiz-Reyes N. A honey bee foraging approach for optimal location of a biomass power plant. Applied Energy 2010;87(7):2119–27.
[162] Bozbas K. Biodiesel as an alternative motor fuel: production and policies in the European Union. Renewable and Sustainable Energy Reviews 2008;12(2):542–52.
[163] Sharma YC, Singh B. Development of biodiesel: current scenario. Renewable and Sustainable Energy Reviews 2009;13(6–7):1646–51.
[164] Wiesenthal T, Leduc G, Christidis P, Schade B, Pelkmans L, Govaerts L, et al. Biofuel support policies in Europe: lessons learnt for the long way ahead. Renewable and Sustainable Energy Reviews 2009;13(4):789–800.
[165] Naik SN, Goud VV, Rout PK, Dalai AK. Production of first and second generation biofuels: a comprehensive review. Renewable and Sustainable Energy Reviews 2010;14(2):578–97.
[166] Damartzis T, Zabaniotou A. Thermochemical conversion of biomass to second generation biofuels through integrated process design—a review. Renewable and Sustainable Energy Reviews 2010, doi:10.1016/j.rser.2010.08.003.
[167] Alfonso D, Perpiñá C, Pérez-Navarro A, Peñalvo E, Vargas C, Cárdenas R. Methodology for optimization of distributed biomass resources evaluation, management and final energy use. Biomass and Bioenergy 2009;33(8):1070–9.
[168] Agugliaro FM. Gasificación de residuos de invernadero para la obtención de energía electrica en el sur de España: Ubicación mediante SIG. Interciencia 2007;32(2):131–6.
[169] Puig-Arnavat M, Bruno JC, Coronas A. Review and analysis of biomass gasification models. Renewable and Sustainable Energy Reviews 2010;14(9):2841–51.
[170] Madlener R, Antunes CH, Dias LC. Assessing the performance of biogas plants with multi-criteria and data envelopment analysis. European Journal of Operational Research 2009;197(3):1084–94.
[171] Fridleifsson IB. Geothermal energy for the benefit of the people. Renewable and Sustainable Energy Reviews 2001;5(3):299–312.
[172] Mahmoudi H, Spahis N, Goosen MF, Ghaffour N, Drouiche N, Ouagued A. Application of geothermal energy for heating and fresh water production in a brackish water greenhouse desalination unit: a case study from Algeria. Renewable and Sustainable Energy Reviews 2010;14(1):512–7.
[173] Omer AM. Ground-source heat pumps systems and applications. Renewable and Sustainable Energy Reviews 2008;12(2):344–71.
[174] Dagdas A. Heat exchanger optimization for geothermal district heating systems: a fuel saving approach. Renewable Energy 2007;32(6):1020–32.
[175] Tselepidou K, Katsifarakis KL. Optimization of the exploitation system of a low enthalpy geothermal aquifer with zones of different transmissivities and temperatures. Renewable Energy 2010;35(7):1408–13.
[176] Lagorse J, Paire D, Miraoui A. Sizing optimization of a stand-alone street lighting system powered by a hybrid system using fuel cell. PV and battery. Renewable Energy 2009;34(3):683–91.
[177] Deshmukh MK, Deshmukh SS. Modeling of hybrid renewable energy systems. Renewable and Sustainable Energy Reviews 2008;12:235–49.
[178] Kalantar SM, Mousavi G. Dynamic behavior of a stand-alone hybrid power generation system urbine, microturbine, solar array and battery storage. Applied Energy 2010;87(10):3051–64.
[179] Klychev SI, Mukhammadiev MM, Zakhidov Ra, Potaenko KD. Technical and economic conditions for creation of combined solar-wind power plants. Applied Solar Energy 2007;43(4):214–7.
[180] Moura PS, De Almeida AT. Multi-objective optimization of a mixed renewable system with demand-side management. Renewable and Sustainable Energy Reviews 2010;14(5):1461–8.
[181] 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. IE Transactions on Renewable Power Generation 2010;4(5):404–19.

[182] Mahor A, Prasad V, Rangnekar S. Economic dispatch using particle swarm optimization: a review. Renewable and Sustainable Energy Reviews 2009;13(8):2134–41.
[183] Brini S, Abdallah HH, Ouali A. Economic dispatch for power system included wind and solar thermal energy. Leonardo Journal of Sciences 2009;14:204–20.
[184] Bernal-Agustín JL, Dufo-López R, Rivas-Ascaso DM. Design of isolated hybrid systems minimizing costs and pollutant emissions. Renewable Energy 2006;31(14):2227–44.
[185] Dufo-López R, Bernal-Agustín JL. Multi-objective design of PV-wind-diesel-hydrogen-battery systems. Renewable Energy 2008;33(12):2559–72.
[186] Ould B, Sambou V, Ndiaye PA, Kébé CMF, Ndongo M. Optimal design of a hybrid solar-wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP). Renewable Energy 2010;35(10):2388–90.
[187] Bilal BO, Sambou V, Ndiaye PA, Kébé CMF, Ndongo M. Optimal design of a hybrid solar–wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP). Renewable Energy 2010;35(10):2388–90.
[188] Montoya FG, Baños R, Gil C, Espín A, Alcayde A, Gómez J. Minimization of voltage deviation and power losses inpower networks using Pareto optimization methods. Engineering Applications of Artificial Intelligence 2010;23:695–703.
[189] Cormio C, Dicorato M, Minoia A, Trovato M. A regional energy planning methodology including renewable energy sources and environmental constraints. Renewable and Sustainable Energy Reviews 2003;7(2):99–130.
[190] Courtecuisse V, Sprooten J, Robyns B, Petit M, Francois B, Deuse J. A methodology to design a fuzzy logic based supervision of hybrid renewable energy systems. Mathematics and Computers in Simulation 2010, doi:10.1016/j.matcom.2010.03.003.
[191] Kaviani AK, Riahy GH, Kouhsari SHM. Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages. Renewable Energy 2009;34(11):2380–90.
[192] Eke R, Kara O, Ulgen K. Optimization of a wind/PV hybrid power generation system. International Journal of Green Energy 2005;2(1):57–66.
[193] Giannakoudis G, Papadopoulos AI, Seferlis P, Voutetakis S. On the systematic design and optimization under uncertainty of a hybrid power generation system using renewable energy sources and hydrogen storage. Computer Aided Chemical Engineering 2010;28:907–12.
[194] Sreeraj ES, Chatterjee K, Bandyopadhyay S. Design of isolated renewable hybrid power systems. Solar Energy 2010;84(7):1124–36.
[195] Bernal-Agustín JL, Dufo-López R. Simulation and optimization of stand-alone hybrid renewable energy systems. Renewable and Sustainable Energy Reviews 2009;13:2111–8.
[196] Senjyu T, Hayashi D, Yona A, Urasaki N, Funabashi T. Optimal configuration of power generating systems in isolated island with renewable energy. Renewable Energy 2007;32(11):1917–33.
[197] Balamurugana P, Ashok S, Jose TL. Optimal operation of biomass/wind/PV hybrid energy system for rural areas. International Journal of Green Energy 2009;6(1):104–16.
[198] Nema P, Nema RK, Rangnekar S. A current and future state of art development of hybrid energy system using wind and PV-solar: a review. Renewable and Sustainable Energy Reviews 2009;13(8):2096–103.
[199] Dufo-López R, Bernal-Agustín JL, Contreras J. Optimization of control strategies for stand-alone renewable energy systems with hydrogen storage. Renewable Energy 2007;32(7):1102–26.
[200] Garcia RS, Weisser D. A wind-diesel system with hydrogen storage: joint optimization of design and dispatch. Renewable Energy 2006;31(14): 2296–320.
[201] Koutroulis E, Kolokotsa D, Potirakis A, Kalaitzakis K. Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms. Solar Energy 2006;80(9):1072–88.
[202] Yang H, Zhou W, Lu L, Fang Z. Optimal sizing method for stand-alone hybrid solar-wind system with LPSP technology by using genetic algorithm. Solar Energy 2008;82(4):354–67.
[203] Del Real AL, Arce A, Bordons C. Optimization strategy for element sizing in hybrid power systems. Journal of Power Sources 2009;193(1): 315–21.
[204] Bernal-Agustín JL, Dufo-López R. Efficient design of hybrid renewable energy systems using evolutionary algorithms. Energy Conversion and Management 2009;50(3):479–89.
[205] Zervas PL, Sarimveis H, Palyvos JA, Markatos NCG. Model-based optimal control of a hybrid power generation system consisting of photovoltaic arrays and fuel cells. Journal of Power Sources 2008;181(2):327–38.
[206] Diaf S, Belhamel M, Haddadi M, Louche A. Technical and economic assessment of hybrid photovoltaic/wind system with battery storage in Corsica island. Energy Policy 2008;36(2):743–54.
[207] Hakimi SM, Moghaddas-Tafreshi SM. Optimal sizing of a stand-alone hybrid power system via particle swarm optimization for Kahnouj area in south-east of Iran. Renewable Energy 2009;34(7):1855–62.
[208] Razak JA, Sopian K, Ali Y, Alghoul MA, Zaharim A, Ahmad I. Optimization of PV-wind-hydro-diesel hybrid system by minimizing excess capacity. European Journal of Scientific Research 2009;25(4):663–71.
[209] Chakraborty S, Senjyu T, Saber AY, Funabashi T. Optimal thermal unit commitment integrated with renewable energy sources using advanced particle swarm optimization. IEEJ Transactions on Electrical and Electronic Engineering 2009;4:609–17.
[210] Matevosyan J, Olsson M, Söder L. Hydropower planning coordinated with wind power in areas with congestion problems for trading on the spot and the regulating market. Electric Power Systems Research 2009;79(1): 39–48.
[211] Castronuovo ED, Lopes JAP. On the optimization of the daily operation of a wind-hydro power plant. IEEE Transactions on Power Systems 2004;19(3):1599–606.
[212] Jurado F, Saenz JR. Neuro-fuzzy control for autonomous wind-diesel systems using biomass. Renewable Energy 2002;27(1):39–56.
[213] Dufo-López R, Bernal-Agustín JL. Design and control strategies of PV–diesel systems using genetic algorithms. Solar Energy 2005;79(1):33–46.
[214] Anagnostopoulos JS, Papantonis DE. Simulation and size optimization of a pumped–storage power plant for the recovery of wind-farms rejected energy. Renewable Energy 2008;33(7):1685–94.
[215] Anarbaev AI, Zakhidov RA, Avezov RR. Schematic and parametric optimization of solar + fuel boiler installations. Applied Solar Energy 2008;44(1): 20–3.