

COMPUTATIONAL OPTIMIZATION METHODS FOR RENEWABLE AND SUSTAINABLE ENERGY SYSTEMS: A COMPREHENSIVE REVIEW

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Abstract

Social and economic development depends on sustainable energy as one of the important inputs. The demand of energy has therefore risen drastically due to the generalization of agricultural, industrial and domestic activities particularly in the emergent nations. This has translated to fast acceleration in the amount of the greenhouse gas emissions and the rise in fuel prices that are the primary driving factor behind the push to harness renewable energy sources more optimally, i.e. the energy that is produced by natural resource and also naturally replenished. Although the benefits of renewable energy are apparent, it also has significant demerits, including the lack of consistency in production, since a majority of the renewable energy sources are climate-dependent, and that is why their utilization needs sophisticated design, planning, and optimization of control strategies. Fortunately, with the ever-growing developments in computer hardware and software's, researchers are getting access to these optimization problems through the use of computational resources, which is illustrated by the fact that there are many optimization methods that have been implemented in the renewable and sustainable energy sector. The paper provides the analysis of the latest state of the art in numerical optimization procedures used in renewable and sustainable energy that can help to see the recent research developments in this area.

Keywords: *Renewable energy systems Optimization, Multi-criteria decision analysis, Computational optimization, Metaheuristic algorithms, Multi-objective (Pareto) optimization*

1. Introduction

With the growing world economy, the world energy demand has been increasing at a very high rate and in the emerging markets. This increase follows two related facts: the conventional fossil resources are limited, and their exploitation is a cause of climate change in terms of carbon emission into the atmosphere[1]. The decreasing reliance on fossil fuels is mostly sought in two strategies. The former is aimed at reducing the consumption through the adoption of energy-saving initiatives and enhancing the energy efficiency of industrial [2] and domestic [3] types of spheres.

The second pathway is to augment the portion of renewable energy, not only in large scale power production but in standalone systems[4]. Although many people consider renewable technologies as less competitive compared to traditional electricity conversion methods, primarily due to intermittency and rather high maintenance needs, renewables have still found their way to the benefits table. These are less dependence on fossil resources and less carbon emission to the atmosphere[5]. Moreover, renewables do not present the safety issue related to atomic power that has played a role in enhancing greater public acceptance of renewable power plants in most of the locations[6, 7]. One of the practical decisions that governments and companies can be confronted with is whether a renewable energy system fits a specific location and, in this case, what technology (or mix of technologies) is the best.

To justify such choice, a number of authors have made comparisons of renewable technologies on the basis of sustainability. An example is Evans[8] who compared wind power, hydropower, photovoltaic and geothermal on the basis of the cost of the electricity generated, lifecycle greenhouse gas emissions, the availability of resources, the facility conversion efficiency, land usage, amount of water used, and their effects on people. Meng [9] has documented that wind energy is linked with the fewest comparative greenhouse gas emission, the least amount of a requirement of water and has positive social impacts detailed yet stated that wind can occupy more land and it might have higher capital cost[10]. In a broader sense, sustainable development of renew- was examined through the lens of the three important technology changes, namely, the demand-side energy conservation, the enhanced efficiency on the production front, and the replacement of the fossil fuel with renewable energy sources. The recent research has been going on to analyze the energy, economical, and environmental implication of the renewable systems such as those provided by [4] and [8].

Better innovations of renewable energy technologies will also help in sustainable development and offer a remedy to some of the environmental issues associated with energy[11]. In this regard, optimization algorithms offer a viable means of solving complex decision making in renewable energy systems. According to the Scopus data presented in Fig. 1, the search results indicate that the number of research works dedicated to the use of optimization algorithms in the topics of renewable energy addressed in this paper has increased fast[12]. A wide range of optimization-based models have been reviewed by other authors - renewable-energy system models, emissions-mitigation models, energy-planning models, supply-demand balance models, forecasting models, and control/operation models[13], but there are still new models appearing in the renewable energy literature. It is on this basis that the paper will offer a revised discussion on the methods of optimization that have been adopted recently in the renewable energies.

2. Brief Review of Single and Multi-Objective Optimization

In mathematics, optimization is the act of minimizing or maximizing the value of a function under a set of constraints using inputs to the function[14]. Combinatorial optimization is a subdivision of optimization, which addresses problems with discrete decision variables[15]. Computational optimization may be defined as designing, implementing, and testing of algorithms to provide solutions to a large variety of optimization problems. It applies mathematics to model it, operations research to present the system, computer science to model and analyze algorithms, and software engineering to put solutions into practice and to test them[16]. Developments in algorithm design and computer architecture have enabled the solution of most problems that arise in real-world situations[17], formerly assumed intractable.

The term optimization has connotations of seeking a real optimum but the reality in most practical situations is that it is not possible to achieve an optimum. Many real optimization problems are in NP-hard classes[18]. i.e. there is no known algorithm that can be run in the polynomial-time that ensures the global optimum. In the worst, precise algorithms can take exponential time, which can easily be impractical in real systems. It is against this reason that numerous scholars have suggested inexact methods of implementation on behalf of classical exact methods like linear-programming (LP), Nelder Mead Simplex (NMS) method[19], Lagrangian relaxation (LR), quadratic programming (QP) and other such methods. The metaphorical heuristics can be considered more an extensive levels of heuristics: they are meant to be applicable to a wide range of problem domains, and only a small amount of adaptation is often necessary to implement them in a new environment[20]. Nevertheless, there are still some issues that are too computationally difficult to be solved using heuristic and meta-heuristic methods without incurring good solutions in reasonable run-time. Parallel processing has become an appealing trend in such instances in an effort to enhance the quality of solution as well as minimizing run-time[21].

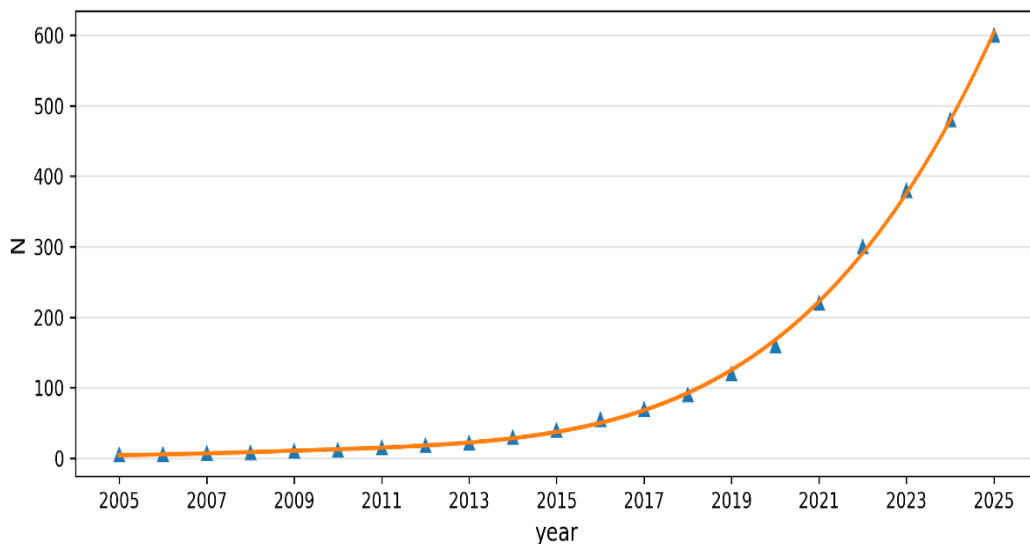


Fig. 1. Number of articles published over the past 20 years that apply optimization algorithms to renewable energy (excluding review papers)

The meta-heuristics are usually categorized as follows. A common difference exists between population-based methods and trajectory-based methods. Other classifications are between memory based and memory less and nature based and non-nature based. Trajectory meta-heuristics are the ones that search in the pursuit space in a one-solution-at-a-time manner and generally provide one solution as an ultimate to be optimized. Most of these techniques are variants of iterative improvement programs that provide means of local optima escape. Trajectory-based meta-heuristics Examples Trajectory-based meta-heuristics are hill climbing (HC), simulated annealing (SA), tabu search (TS), greedy randomized adaptive search procedures (GRASP), variable neighborhood search (VNS), and iterated local search (ILS) among others[22].

In contrast, population-based meta-heuristics keep and develop a pool of candidate solutions (population). The working population is updated by a series of procedures and the algorithm that gives a population (or a selected fraction of it) upon reaching a stop criterion. Population-based meta-heuristics that are commonly used are 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), and others[23-25].

Also important to mention, is that numerous computational optimization techniques have traditionally been used to single-objective problems either with or without constraints. In real life, however, most applications need to optimize a number of objectives simultaneously which can conflict among themselves. It is because of this reason that multi-objective algorithms have been suggested[26]. The multi-objective methods can be generally divided into two primary groups, which are the methods depending on aggregate weight functions and the other methods depending on Pareto-based optimization. Aggregating functions are used to bring together all the objectives to a single scalar objective and the relative weight of each objective is captured by weights[27]. This method is conceptually straightforward but has certain disadvantages such as the identification and tuning of weights are not easy, particularly when objectives are measured in different units and scales. Moreover, with aggregation, there will be only one final solution, which may hinder the decision making in case there are more than one viable alternatives.

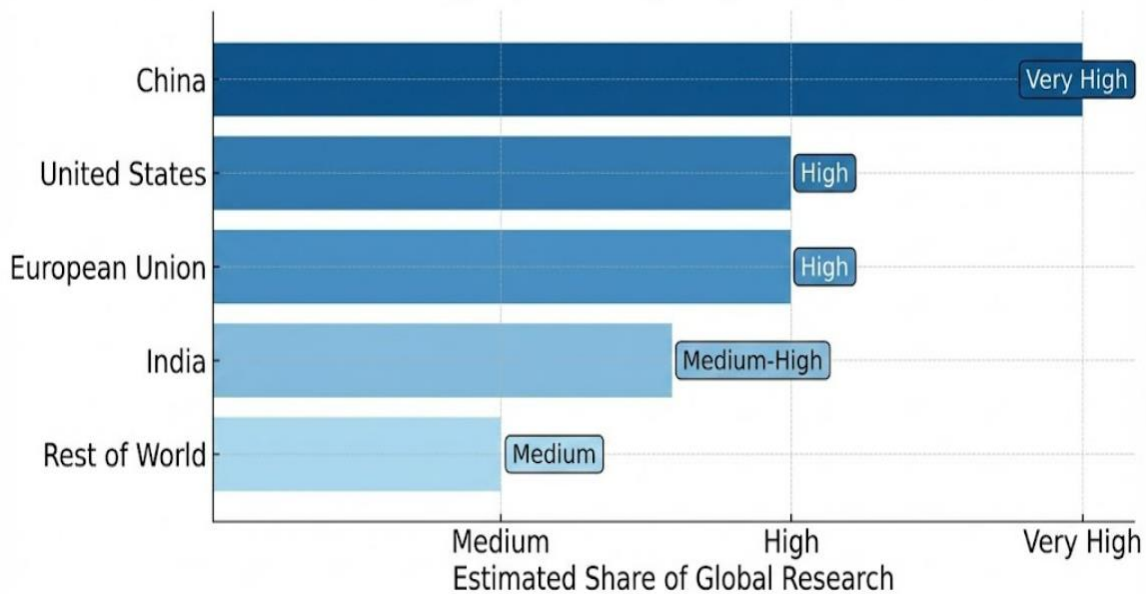
These constraints encourage Pareto-based multi-objective optimization[28], which is a comparison of the solutions on the basis of Pareto dominance. Solutions to a multi-objective optimization problem, involving $K \geq 2$ or more objectives, are not associated with a single scalar value, but are partially ordered, based on elements of dominance relationships. A solution s_1 is said to dominate another solution s_2 via the fact s_1 is not worse off s_2 in any objective and it is strictly better in at least one objective. Two solutions are indifferent when none of the solutions dominates the other. The Pareto optimal set is comprised of the set of solutions that is not dominated by other solutions. This set in most situations has more than a single optimum. Given the fact that the objectives are considered equally significant, multi-objective optimization aims to discover the full Pareto set or a representative sample of the same.

In the last decades a great number of multi-objective meta-heuristics were presented. It is possible to describe them in terms of the trajectory-based distinction and the population-based one. The examples of trajectory techniques are the Pareto archived evolution strategy (PAES) and multi-objective simulated annealing (MOSA). Multi-objective 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 (and Pareto envelope-based selection algorithm (PESA/PESA-II) are all population-based methods. They have suggested hybrid methods, combining two or more techniques including genetic tabu search (GTS), multi-objective genetic local search (MOGLS), memetic-PAES (M-PAES) and multi-objective simulated annealing and tabu search (MOSATS) among others [29, 30].

Taking into account the data presented in the ISI web of knowledge, Fig. 2 demonstrates the number of papers involving the utilization of optimization algorithms reported in this section and used in renewable energy by country. It establishes that researches in 10 countries cover this line of research.

Estimated Distribution of Research Papers on Optimization Algorithms in Renewable Energy by Country/Region (Up to 2025)



Note: Distribution based on qualitative analysis of current academic and industry reports.

Fig. 2. Country-wise distribution of published research papers applying the optimization algorithms reviewed in this study to renewable energy systems.

3. Optimization techniques applied to renewable and sustainable energy systems

The energy resources have an effect on the economic performance and the political stability of the country, that is why any changes in the technological basis of energy systems are not only significant, but are also quite challenging to be avoided. This leaves researchers with an ongoing need of assessing the way the energy systems ought to be developed[31]. Optimization methods have been suggested as useful in addressing decision problems within a renewable energy system in most of the published works. These techniques are discussed in this paper in terms of design, planning, and control, as discussed below.

Due to the constant growth of the energy demand globally, the development of the distribution networks and the incorporation of the new sources of the generation have become significant concerns. Considering the expensive nature of the infrastructure of renewable energy that has a direct relation to costs of investment, long-term design and planning is usually directed to choose the most appropriate choice between several renewable options[32, 33]. Community level planning is particularly more challenging since it involves justification of how energy resources and services are to be divided, establishment of local policies that bring together energy consumption to economic growth and energy structure, and a good balance between economic cost, system reliability, and energy-supply security[34].

Structured optimization models such as interval linear programming (ILP), chance-constrained programming, and mixed integer-linear programming (MILP) have been used by several authors to address this complexity. The strategies may produce energy resource/service-allocation plans and capacity-expansion strategies that will minimize the overall system cost and enhance the reliability and energy security[35]. The model of long-term dynamic multi-objective planning of the expansion of the distribution network and distributed energy options were introduced [36] and [37], which were used an immune genetic algorithm-based (I-GA) method to determine optimal sizing, placement schemes and model investment dynamics in distributed generation units and network reinforcement over a planning horizon. There are also multi criteria decision-making process founded on fuzzy technique that have defined the most appropriate renewable energy options[38]. Besides that, [39] also examined significant computer based tools that were employed to determine renewable energy integration into various energy systems with varying goals.

Some authors have talked of the performance of MIP, GA, SA, and TS in solving minimum-cost expansion problems under carbon emission programs to the transmission network planning[40, 41]. Simultaneously, it has been observed that the number of renewable technologies that has proven itself competitive has remained very limited to date and even then only in certain parts of the world[42]. Some researchers respond to this, suggesting that planning schemes should be figured out through Pareto-based multi-objective optimization, in which certain power generation technologies, such as photovoltaic, wind turbine, fuel cell, micro turbine and gas turbine and reciprocal engine, are compared.

An ILP-based optimization model along with two-stage programming superiority-inferiority-based and fuzzy-stochastic programming yields decision alternatives and assistance to decision makers under various economic and system-reliability restrictions,[43] were proposed in long-term renewable energy management planning. As indicated in [44], several possibilities of renewable energy were compared to different levels of sustainability. Verma and R. Bhatia[45] applied PSO to predict the annual peak load in electrical power systems, in a bid to reduce the error in the estimation of parameters in the forecasting model. An energy flow optimization model was proposed and used LP to identify the contribution of generation and energy efficiency actions, with taking into consideration main energy exploitation, power and heat generation, emissions, and end-use sectors [46]. In addition to these, other scholars have been working on the development of heuristic optimization algorithms to be used in the realization of more cost efficient energy conversion systems[47].

Table. 1. Optimization method families used in renewable-energy studies

Method family	Examples	Strengths	Limitations	Where used most
Classical deterministic optimization	LP, MILP, QP, Lagrangian relaxation, Simplex (Nelder–Mead)	Fast, interpretable, strong for convex/linear models	Can struggle with nonlinear/nonconvex, may get local optima	Dispatch, unit commitment, sizing with linear models
Heuristic / metaheuristic	GA, PSO, ACO, DE, SA, TS	Handles nonconvex, discontinuous, mixed variables	Parameter tuning needed; computationally heavy	Hybrid sizing, siting, multi-constraint design
Multi-objective optimization	Pareto methods, MOEA, SPEA, NSGA-type approaches	Produces trade-off set (cost–emissions–reliability)	Choosing final point requires decision criteria	Hybrid systems, dispatch with emissions
AI-assisted optimization/control	Fuzzy logic, neuro-fuzzy, ANN-supported models	Captures nonlinear behavior; useful in control	Requires data/training; may reduce interpretability	Control of wind–diesel, forecasting + operation
Parallel / accelerated computing	Parallel GA/PSO, distributed evaluation	Speedup for large search spaces	Underused; implementation complexity	Large-scale hybrid sizing, network dispatch

Uncertainty is one of the biggest factors that explain the significance of using new optimization approaches to short-term energy planning[48]. As renewable generation becomes quite penetrated, power systems will require appropriate devices to deal with wind, solar, and hydropower variability and randomness[49]. Generally, optimization problems that concern energy are varied. Indicatively, ANN has been studied in prediction of energy demand[50]. Other works presented a simulator of a renewable energy system that incorporates wind, solar, energy storage and stand-by plants in grid connected and stand-alone operation; the simulator is able to calculate the energy flows and optimize the scheduling decisions of either the stand-by plant or the grid connection. Moreover, researchers have also come up with pre-processing methods and algorithms that are early created to tackle and solve complex real-life scheduling problems like timetabling and labour scheduling and the methods have proven to perform well[51]. There are also multi-criteria nature of energy planning problems that have different decision makers and conflicting objectives. The literature [52-54] contains reviews of multi criteria

decision-making procedures that are used in the context of renewable energy. More specifically in a review of the literature regarding the current state of the art in multi-objective distributed energy resource planning and highlighted that demand-side management and load controllability will probably take centre stage in the future systems where the effects of energy consumption are addressed in a more conscious manner.

Control wise, measurement, and control of the impacts of integration of renewable in power systems and in particular distribution systems are one of the critical issues. A large-scale application of renewable sources is in the electrical sector, although there is one fundamental limitation to electricity generation and consumption, namely, it cannot be easily stored on a large scale, therefore the balance between generation and demand must be maintained in real time. In this regard, various optimization processes to solve the intrusion and congestion control of renewable sources are used[55]. A congestion management model of deregulated power systems was presented, which coordinates the dispatch of pools by bilateral and multilateral contracts negotiated privately, in a manner that maximizes the social welfare[56]. It was also suggested to use a hybrid technique that integrates NMS method and PSO[57], and its results were reported to be more preferable than those of other population-based algorithms which include the original PSO, honey bee mating optimization (HBMO), ANN, ACO, and GA[58]. Despite the growing popularity of the use of renewable sources, it is still a difficult task to incorporate these sources into the energy systems. Applied and reviewed optimization criteria used in an energy system model to investigate the role of heat pumps in integration of wind power is an example[59]. To optimally manage the distribution networks involving the fuel cell power plants, the use of fuzzy adaptive PSO and they have demonstrated better results than GA, PSO, DE, ACO and TS are suggested[60]. The matter of energy storage is another urgent subject matter due to the decoupling of the delivery and the supply time. Therefore, researchers keep investigating the ways to make the storage efficient, as well as its optimal utilization in the energy systems. A multi- objective optimization of load dispatch in power systems that include renewable energy and CO2 capture and storage technologies was also studied[61]. In the case of hybrid systems, that is, energy storage with renewable generation, optimal bidding strategy models have also been provided[62].

Renewable energy is not just useful in power generation as renewable power but it is also employed in multi-purposes like water pumping. The idea of water distribution is also an optimization problem, and the results of its optimization can be more than just significant in environmental terms[63, 64]. Others also discussed the solar photovoltaic pump, windmill pump and dual fuel engine pump that uses biogas to pump irrigation water[65], Other ones examined the use of wind turbines in pumping water either directly by mechanical pumping or indirectly by producing electricity to pump water with electricity[66]. The water supply systems are highly energy consuming which is translated to high energy operating cost [66, 67]. These expenditures are determined by aggregate consumption and the variation in the day-to-day tariffs. On this region, [68] maximized the operation planning of the wind-hydro hybrid water supply systems. Besides these, the greenhouse design, which uses renewable sources of power, has been gaining recognition. Another model is the mixed integer optimization model which was developed to determine when the incorporation of a floor-heating-based greenhouse with a waste-to-energy plant can be economically lucrative[69].

This review proceeds to provide a synopsis of the new developments in optimization algorithms of renewable energy based on the various energy sources.

Table. 2. Summary of optimization applications across renewable and sustainable energy systems.

Renewable energy domain	Typical optimization problems	Key decision variables	Common objective functions	Common constraints	Frequently used methods
Wind energy	Economic dispatch, unit commitment with wind, siting/layout, scheduling	Dispatch levels, on/off status, turbine location, reserve levels	Min cost, min emissions, min losses, maximize reliability	Power balance, ramp limits, network constraints, reserve requirements	LP/MILP, GA, PSO, MOEA, neuro-fuzzy
Solar (PV/thermal)	PV sizing, tilt/angle selection, storage sizing, dispatch	#PV modules, tilt angle, battery capacity, inverter size	Min LCOE/cost, max energy yield, min unmet load	Land/area limits, battery SOC limits, load coverage	GA, PSO, SA/TS hybrids, MILP
Hydropower	Reservoir operation, multi-reservoir scheduling, hydro-wind coordination	Release rates, reservoir levels, turbine output	Max revenue/energy, min spill, min cost	Water balance, environmental flow, transmission constraints	Dynamic programming, EA/MOEA, stochastic optimization
Bioenergy / Biomass	Supply-chain siting, plant location, feedstock logistics, conversion planning	Facility locations, supply radius, feedstock routing, plant capacity	Max profit, min cost, min emissions	Feedstock availability, transport limits, tech constraints	Binary PSO, GA, multi-criteria optimization
Geothermal	Heat exchanger sizing, aquifer exploitation planning, pumping optimization	Heat-transfer area, flow rates, pipe network design	Max annual profit, min pumping + amortization cost	Thermal limits, pumping constraints, network constraints	GA, techno-economic optimization

Renewable energy domain	Typical optimization problems	Key decision variables	Common objective functions	Common constraints	Frequently used methods
Hybrid renewable systems	Sizing + control of PV-wind-diesel-battery/hydrogen, dispatch, reliability planning	PV/wind sizes, storage size, dispatch rules, fuel cell/electrolyzers sizing	Min annualized cost, min emissions, min LPSP, min unmet load	Reliability constraints (LPSP/LOL), SOC, technical limits	MOEA/SPEA, GA, PSO, LP, fuzzy/neuro-fuzzy

3.1. Wind Power

Wind has been considered as a viable alternative source of energy. Nonetheless, the availability of wind cannot be constant over geographically extensive areas and wind behavior is discontinuous over a large area like in Mexico [70]. Simultaneously, the wind sector has become visible. Wind Turbines have become larger and the unit costs of installation have fallen, which implies that previous research and development investments have been converted into better technology and economics [71]. Wider appraisals have also been done of world wind energy potential [72, 73]. The ongoing trends are the further offshore development, the trend to the further use of smaller distributed grid-connected turbines, and their implementation in a broader geographical location. Consequently, researchers keep suggesting and experimenting with new techniques of enhancing the structure and functioning of wind power systems [74]. Even with these developments wind is not either technically or economically viable in all locations, especially in areas with low wind velocities, and its intermittency may render it less dependable than other renewables in practice. The wind farms are usually developed in areas that have stronger and more reliable winds like offshores, high altitude areas[75]. When assessing a wind project, the relevant factors make significant impacts on the performance that can be achieved are their principle of operation of the wind energy system, the correctness of the wind-speed distribution characterization, the site location, and the operational management approach for conversion of wind energy into usable electrical power [76]. The common practice issue is how one should establish the appropriate capacity to invest in, particularly in cases where there are limited or inadequate wind data to develop projects on long term basis. Others have also aimed at estimating the potential wind power at a particular location as it has been historically and determine whether the site is capable of supplying a certain level of demand [77]. A long-term wind speed distribution modeling has also been used with Bayesian model for handling average uncertainty in a better way [78]. A GA-based method where significant wind farm constituents and technological parameters were considered as inputs and the electrical system construction of the wind farm was optimized in terms of cost of production and system durability[79].

Wind farm layout is another research issue of great importance in wind power. In reality, wind research tends to focus on two related design layers wind turbine design, and wind farm layout[80]. The output power at the turbine

level is a physical relation to air density, rotor area covered and wind speed (often, a cubic relation) and this is what drives aerodynamic and structural optimization. The power quality improvement is still developing, and there are a lot of authors who concentrate on the possibility to use tuning of turbine parameters, and to obtain the better working results. These popular power quality measurements are power factor, reactive power behavior, and harmonic distortion. Simultaneously, the manufacturers still grow the average size of turbines used and advance technology, such as gearless versions [81].

Turbine design is often the field of application of multi-objective optimization, as important goals inevitably conflict between themselves. As an illustration, a multi-objective evolutionary algorithm (MOEA) was proposed to optimize rotor geometric parameters in a stall-regulated horizontal-axis wind turbine to find the compromise between the total energy output per unit wind park area and cost[82, 83]. Optimization of the structure of blades has also been examined. The cross-sectional area radius of gyration and length segment were decision variables in a horizontal-axis blade design problem [84, 85] and the optimum was obtained using a maxi- chronic frequency design criterion. Other authors made the system design simpler by removing active electronic parts (power and controlling) and constructing a low-cost all-passive system [86]. Also, good design of laminated composite shell structures, especially wind turbine blades has been gaining increasing interest. In one case, an optimization algorithm was used[87], based on the method of moving asymptotes[88, 89] to solve a related problem, and had also reviewed methods applied in the optimal design of wind turbine blades. Internal drivetrain optimization with GA has also been used [90, 91], which optimized the choice of gear ratio and power ratings in multi hybrid permanent-magnet wind generator systems. Multi-objective formulations based on performance also exist in literature [92], which has created a MOEA in which the quantities to be maximized were the wind power and the minimization of the vibrations of the drivetrain and tower, and the optimum size of the rotor and other parts of stand-alone wind-battery system [93]. Other researchers optimized the wind turbine blades, where the shape parameters, such as chord, twist, relative thickness are varied with the aim of minimizing cost of energy which is determined as a ratio of the yearly energy production to the cost of the rotor[94, 95].

A numerical optimization method along with aero elastic load modelling and site-specific cost model was suggested, whose goal was to minimize cost of energy [83, 96]. On the same note, a minimum energy cost methodology that combines aero elastic analysis and numerical optimization was presented[97]. Data mining has also been used in other works in order to optimize the power output of wind turbines by using evolutionary computation [98, 99]. Suggestions have also been made on decision-analysis frameworks. Mixed integer nonlinear programming (MINLP) is one example that has been used to estimate optimal capacity taking into consideration the uncertainty associated with the distribution of wind speeds and power-speed characteristics [100]. With more and more turbines being deployed, reliability is necessary in ensuring that energy yield is high. In that regard, methods and mechanisms, and optimization algorithms applied in tracking the performance of turbines and identifying faults in their early stages with the aim of preventing disastrous breakdowns were overviewed[101]. This focus is in line with the fact that the capacity of a turbine and its structural size have grown significantly over the last few years.

Wind turbines also have operationally limited cut in and cut out since they can only produce power when in a specified range of wind speed. As the estimation of power in wind is required on the basis of wind speed and system variables, a number of studies have used fuzzy logic modelling to estimate the power curves of wind

turbines [102], and investigated a flutter based flap wind power generator which extract energy on the basis of flutter and multi-objective adaptive neighboring search was used to optimize the power and system efficiency [103].

Layout optimization at the wind farm level involves the arrangement of turbines to ensure maximum energy capture at the farm level with certain constraints such as land area, number of turbines, spacing, cost etc.[104]. A GA was presented to determine turbine positions that were used to realize maximum output with a constraint (number of turbines, cost etc.)[105]. A new code and a new GA objective function was suggested to balance cost, power and efficiency more effectively than the previous methodologies[106]. The optimization of wind farm configuration was done by using an EA, which was motivated by a cost model relying on cumulative net cash flow over the wind farm life[107]. In multi-objective layout problems, a MOEA was suggested that is wind distribution based and that aims at obtaining a maximum amount of wind energy and reducing a second goal, which is the violation of a constraint [108]. The other related problem is turbine selection, in which the aim is to select the combination of types of turbines among a number of available options. Pareto-based analysis was used in order to investigate the performance, failure, and reliability of wind farms[109]. In order to establish optimal kind, quantity and location of turbines, in given wind conditions, and site constraints, MINLP-based methods were developed[110, 111].

The uncertainty of forecasting in wind power operations is also a significant problem and forecast error has the potential to directly affect the bidding strategy and unit commitment in the day-ahead market. In this regard, fuzzy optimization methods have been employed to generate maximum benefits and reduce risk when there is uncertainty [112]. A wind speed prediction scheme was provided, which was based on data of nearby places [113], and a scheme of wind speed prediction was also proposed, but it was based on the adductive networks and demonstrated better and more automated synthesis of models and a clear structure of analytical input and output in comparison with other machine learning methods[114].

Although the forecasting is becoming better, large offshore farms may have power fluctuations which increase more operational and control challenges as the scale of offshore wind power variation should not be regarded as determined solely by the generation level. Statistical regime-switching models analysis demonstrated that the magnitude of the offshore wind power variation cannot be regarded solely as a result of the current generation level [115]. Unpredictability and fluctuations in the wind production have hence inspired regulation and energy control measures. As an example, short-term energy management of wind power plant with battery storage was proposed [116, 117] and their online heuristic is intended to be used in decision-making that is not based solely on historical data and projections. Due to the fact that wind should be optimized to work with the traditional generators, market and operational risks play a role as well, [100, 118, 119] such as the risk management in the electricity market when operating with wind power and examined optimized algorithms relevant to such use that include direct search, PSO, GA, and scenario construction methods.

At the turbine-control level, tuning of rotor speed and tip-speed ratio must be employed to achieve maximum power and energy capture and heuristic techniques like PSO have been applied towards this purpose [120-122] Even though wind production does not produce harmful gases, when combined with thermal dispatch, it can occasionally raise emissions, especially at times of low to medium demand, based on dispatch limits and ramping

characteristics. A multi-objective energy dispatch model was proposed, which considers the environmental impact and fuel cost [123]. In case of hybrid setups, fuzzy-linear-quadratic regulator controller was used to enhance quality of power and reject disturbance as the wind speed and load varied [124]. More sophisticated ideas have also been presented. A multi-objective intelligent control framework was outlined, which points at data mining, model predictive, and evolutionary control by taking into account five optimization goals and wind speed, turbulence intensity, and electricity demand as control variables [125]. Lastly, a better structure design of building systems was outlined to strong wind excitation, such as the number of actuators, actuator layout and control algorithms of active type, with a multi-level GA [126-129].

3.2. Solar Energy

The radiant energy that is produced by the sun is known as solar energy and direct solar radiation can be termed as a potent source of energy in most regions across the world. In general, the use of solar in most cases is brought up in two ways; passive and active solar design. Passive solar design revolves around the design of buildings that help in the capture and control of solar gains in order to minimize the use of artificial lighting and space heating. In passive systems, one of the research directions has been optimization and design of solar houses [130]. Since the designing of energy efficiency is one of the primary concerns of the world, the choice of conservation strategies is inherently a multi-criteria decision problem, the decision makers have to make a compromise between a number of goals that are usually mutually conflicting as energy consumption, financial costs and environmental functioning [131]. Active solar design, on the other hand, transforms the solar radiation into useful power by using solar technologies like the photovoltaic cells and solar thermal water-heating devices.

In case of passive and active development of a solar system, some trustworthy data on radiation of the target location is needed. Practically, solar radiation is typically measured with a network of radiometric stations, but the spatial resolution of such networks is typically low. In areas with restricted spatial variability, interpolation or extrapolation may suffice, but in more complicated terrain, they are less precise due to the possibility of a greater change in radiations between measurement locations. To this end, an ANN-based methodology was described to predict solar radiation on difficult mountainous landscape and terrain by applying data of one radiometric station [132, 133]. The other techniques applied in predicting solar irradiation are neuro-fuzzy inference systems [134,135]. Despite the use of better prediction models it is still difficult to obtain the planning relevant information out of radiation datasets, and thus ANN-based approaches have also been suggested to find and optimize the statistics describing the solar radiation availability [136]. Stand-alone photovoltaic systems require storage of energy since solar power is not constant and storage is required to ensure constant supply. Further implementation of these systems is directly associated with the attainability of acceptable capital and operating storage technology costs [137]. In the grid-linked photovoltaic market, accelerated price falls, and dynamic market dynamics have sent the industry to the path of consolidation, scale, and a greater focus on the project development [138]. Regarding optimization, ANN and GA were used to maximize the economic value of a solar energy system [139, 140]. In their treatment, an ANN is trained to capture the correlation between collector area and storage tank size and the resulting auxiliary energy demand; lifecycle savings are estimated and GA is employed to find the best value of the two design variables to maximize lifecycle savings. In monitoring photovoltaic modules, [141-143]. An optimization model was developed to calculate the amount of energy produced by tracking photoelectric power modules and predicting the optimal version of solar module layout

across various locations, and the area of ground needed by single tracking photoelectric power module sacrificing the size to model the energy generated and also to model the optimum module layout at various sites, taking into consideration the land area requirements and layout trade-offs[144]. A research on the optimization of geometrical was applied in the parabolic cylinder receiver system of thermal power plants they infer that the geometry of the parabolic cylindrical concentrator in the system can be optimized to optimum opening angles to provide greater sun concentration[145],

In addition to PV, a number of studies are concerned with solar thermal collectors and concentrating systems. A summary of the parabolic-trough collectors is provide that have been constructed and sold within the previous century and the prototypes that are being developed at the moment[146]. The issues of optimality of the performance of a solar collector through appropriate determination the area of the collector per unit of heat demand, the diameter of the collector pipes and the spacing of the collector pipe axes in the collector plate are also addressed[147, 148]. GA is used to optimize a thermal performance of flat plate solar air heaters, with regard to the various system and operating parameters [149]. The hybrid approach was developed is a hybrid of PSO and non- linear time-varying evolution to calculate the tilt angle of photovoltaic modules to achieve the desired electrical energy output of the modules[150] [151]. A GA based algorithm came also to estimate the electrical parameter of the photovoltaic cells and modules and also calculate the associated maximum power point on the illuminated of current voltages characteristic[152]. Besides, an optimization strategies of the design of the linear concentrating solar collector by stochastic programming and Monte Carlo was proposed to analyze the performance and then minimize an objective function by using a modified Kiefer Wolkowitz algorithm with the control variables being the sample size and step size[153] and [154].

The size of the system is another significant practical problem in photovoltaic systems. The optimization of stand-alone PV systems is a complicated issue since it should meet both technical and economic objectives such as acceptable quality of supply to the consumer at an affordable cost. Performance of artificial intelligence techniques in sizing stand-alone PV, grid-connected PV, and PV–wind hybrid systems was compared[155]. PV sizing via ANN and GA has also been implemented [156, 157]. In the case of hybrid solar-wind power generation including battery storage, a sizing methodology was suggested that targets to optimize the sizes of the main components [158]. The sizing optimization of stand-alone PV systems using hybrid technology of energy storage was also focused[159]. The optimization of stand-alone PV systems was conducted to minimize the gross energy needs through the minimization of the storage capacity in the optimization of NSGA- II [160]. Optimization of grid-connected PV systems may be defined as follows: given the list of commercially available devices, we are to choose the best number and type of devices and the best details of installation in such a way that the net economic benefit of the system over its lifetime is maximal [161]. This kind of decision problem has also been the subject of application of PSO. This problem was also approached with the application of PSO by adoption of two levels of approaches, such as control of a distributed solar collector field by fuzzy logic and physical model-based optimization [162, 163]. The obtained results showed that the automatic control of the plant and the possibility to use solar performance and stay within its operating limits are possible. Neuro-fuzzy algorithm was used in the daily optimum operation of the household photovoltaic panel generation without storage equipment [164]. Energy generation in photovoltaic system must be optimized so that photovoltaic cells may work at the maximum power point based on the maximum efficiency basing on the irradiation and cell temperatures. An

adaptive perturb and observed method which has fast dynamics and a better stability has also been suggested [165]. The solar energy can also be used to heat water. In centralized solar water heating systems, an EA was adopted to maximize energy saving in solar heating as opposed to conventional domestic electric heating in high rise buildings [166]. Lastly, the water replenishment profile was maximized in a study to maximize the total system performance[167-169].

Hydropower

Hydropower (also known as hydraulic power and water power) is energy derived by taking advantage of flowing water. Since water is very much dense as compared to air, even relatively slow flows of rivers or moderate swells of the sea can contain large amounts of energy. Practically, water power encompasses a number of technologies, but it is commonly referred to as hydroelectricity, which uses the gravitational power of falling and flowing water to generate electricity, and ocean energy, which most commonly means energy derived through ocean waves and tides.

The past decades, the development and regulation of hydropower plants became a subject of more interest [170]. In the case of small run of river hydro power generating facilities, cost effectiveness is closely associated with the size of the plant[171, 172]. In order to solve sizing decisions at realistic operating conditions, stochastic EA was proposed to calculate the optimal size of small hydropower plant; their model is the annual operation as a detailed model and aims to reach a better economic value and maximize the energy production[173].

Temporal series forecasting has also been used to estimate capacity of mini-hydro plants [174, 175]. Besides these, an LP model was experimented in the maximization of hydropower energy generation and investigated the impact of reservoir storage capacity and model sensitivity on the obtained optimal solutions [176]. In electricity markets with deregulation, producers of hydroelectric power would tend to maximize their revenue and deal with the market risk. Specifically, the variability in profits can be a major issue when some uncertainty exists in spot prices and uncertainty in the inflows of reservoirs. In this regard, review of hydropower operation in the case of profit risk and provided future research and application directions was introduced[177]. Similar studies were done in related work, which considered deterministic and stochastic mathematical models that are aimed at maximizing profits realized as a result of selling electricity produced by multiple dams and reservoirs in a deregulated market [178],

Numerical discoveries of historical data have confirmed this advantage of the stochastic models compared to deterministic models. As a case of the multi-objective decision making in water-energy systems, a multi-objective combinatorial optimization model was introduced with an intention to investigate the ecological-economic trade-offs in the choices of dam removal with the objective of minimizing the losses in hydropower and maximizing the storage capacity[179]. The other significant operation activity is the daily hydrothermal generation scheduling, which decides how much power should be produced by the hydro and thermal units on a daily basis, and meet the hydro unit, thermal plant, and power system constraints. This problem has been solved using heuristic methods, such as a Modified Adaptive PSO algorithm [180]. A different formulation has been proposed, which dealt with optimal time scheduling of hydropower plants in a hydrothermal interconnected system by Lagrangian relaxation (LR) and sequential quadratic programming (SQP). Portfolio-oriented planning Hydropower portfolio

management under medium-term uncertainty was proposed in both market price [181] and inflows was modeled using a stochastic LP framework, introduced by [182].

Findings in this regard show that both price and inflow uncertainty need to be clearly stated in the portfolio management models. To calculate the short-term operation of hydropower, a non-linear programming scheduling model was proposed to optimize the unit commitment (start-ups and shut-downs scheduling) and the generation dispatch (hours-hourly power output) of the committed units[183]. According to their findings, the model is able to produce viable locally optimal schedules with consideration of unit status (on/ off) and hourly generation targets to maximize earnings. In another work, a hybrid NMS and PSO method has also been used to solve unit commitment problem [184]. Other approaches like stochastic programming have also been used [185]. PSO demonstrated good performance of short-term scheduling of a hydroelectric generation in power systems where wind turbine generators are present[186]. In the case of cascade hydropower stations, the problem of load allocation is shifted to the multistage, multidimensional dynamic optimization problem. To mitigate this, an immune algorithm was used to optimize load on cascade stations and found that there is good convergence accuracy and reasonable allocation of loads[187].

Hydropower reservoir operation is an ongoing decision process, which is usually the quantity of water to discharge and the quantity to keep in storage. As a matter of fact, the operation of a reservoir is usually bound by operating rules and policies that are set within the strategic plan. Fuzzy rule-based model was developed and tested on the reservoir operation where the rules were formed based on the theoretical or desired storage level[188]. Maintenance Timetable is another practical problem in hydropower systems. In current storage conditions and forecasted inflows, the utilities can reduce the maintenance duration or delay maintenance when there is a concern of unserved energy. In this regard, the maintenance scheduling based on the mixture of ACO and power plant maintenance scheduling method are discussed[189].

Ocean energy

The appeal of wave energy, like other ocean-based renewable energy sources (such as tidal and Stream Energy) is based on good physical features and relative predictability. Wind currents exert action over open water to produce the sea waves, although the potential of wave energy differs extensively by the area, that is, not every area is a good location to exploit wave-power[190]. Just like the case of wind-speed prediction used in wind power planning, water level and wave condition prediction is also a vital requirement of ocean energy systems. Indicatively, an ANN was designed to forecast water levels at a coastal inlet based on the long-term water level measurements[191]. To predict the parameters of the waves, an adaptive network was used based fuzzy inference system in comparison to a coastal engineering manual system [192]. Besides that, it has compared the time-series model predictability with the wave energy production through a hybrid methodology that integrates ANN and wave energy production through time-varying regressions. Another design variable is device-array layout: [193] which has analyzed the impact of the spatial layout of wave energy devices on overall power production using the Parabolic Intersection model and GA, with results showing that GA is capable of providing superior solutions than the Parabolic Intersection model, but at a greater computational cost[194]. The obtained results indicate that the better results can be achieved with the help of GA in comparison to the Parabolic Intersection method, whereas, more computational effort is to be used.

Technologies in ocean energy cover wave energy, tidal energy (barrages, turbines and ocean thermal energy conversion energy [110]. In wave energy conversion, a stochastic optimization problem of a system making use of waves was presented to power an air turbine [195], in which the decision variable was the turbine size (in the form of rotor diameter) and the primary objectives were electrical power generation and annual profit [196]. The other design problem that recurs and occurs is optimization the shape of wave energy collectors to extract more energy; this problem has frequently been carried out heuristically like with GA [197]. In the case of marine current turbines, NMS was employed in design and optimization, which depended on the tidal data, [198-200].

3.3. Bioenergy

Bioenergy is defined as the renewable energy that is in a form of biological resources. Here biomass organic matter of living or recently living organisms such as plant and animal matter are frequently pointed out as a potential renewable modality. Nonetheless, more research and development is required to establish the technicality and cost competitiveness of large-scale biomass-based power generation. Direct utilization of biomass through combustion can be utilized to generate electricity by using the generated steam or generate heat to be used in industries and homes. It may also be converted to form energy carriers like methane (biogas), ethanol and biodiesel. The biomass-powered plants are already being used in numerous countries, and they are bringing an increasing portion of the renewable energy supply. It has been reported that Austria (7%), Finland (20%), and Germany (5%), amongst others, are contributing and biogas-based energy is also gaining ground in Europe. Current developments have seen the growth on solid biomass pellets, the broader implementation of building- or community-scale combined heat-and-power equipment and the expansion of biomass use in centralized the district heating systems [201].

Sustainability of the biomass electricity should be considered in a variety of indicators such as cost, efficiency, greenhouse-gas emissions, availability of resource, operational constraints, land utilization, water utilization, and social implication. Electricity derived bio-mass can usually compete well in cost, efficiency, emissions and availability, and technical issues, but may lose out on high land and water demands and, in certain situations, undesirable adverse social effects [202]. Consistent with such complexities, optimization methods have been actively utilized in biomass energy systems. A binary particle swarm optimization (PSO) algorithm was suggested to locate optimally biomass-fueled distributed generation using forest residues, and they showed better results compared to a genetic algorithm (GA) to maximize a profitability index in the presence of technical constraints. [203, 204] [205]. A multi-biomass conversion application was designed but with optimization framework that takes into account the technical, regulatory, social and logistic constraints. PSO has also been employed to determine the best location of plants and supply zones of biomass power plants and impose limits on the limit of electrical generation [206]. A nature-inspired algorithm was used in discovering biomass plant locations, which provide the investor with the highest profits [207].

The increase in oil prices, uncertainties in supplies, and the need to use cleaner fuels has brought attention back to the use of fuels made of vegetable oils that can be used in diesel engines [208]. Virgin or waste vegetable oils and animal fats can be used as the basis to create biodiesel, which is typically described as being non-toxic, biodegradable and renewable. The main points on the production of bio-diesel were discussed and the overall policy issues were investigated using the experience of the first-mover countries and the long-term cases of biofuel

impacts [209],[210]. The first- and second-generation biofuels were reviewed with a sustainability perspective, including the potential of second-generation pathways including thermochemical conversion of biomass [211]. Since these conversion pathways are not only operationally complex, they have to be exploited efficiently through an integrated process interactions modeling and optimization[212] [88]. In this respect, the approach to optimization of the management and energy use of the distributed biomass resources were introduced, considering both the feedstock characteristics and the size of the plants, the choice of the technologies to be used to produce the power/heat/solid biofuels, the balance of CO₂ and the possible location of the biofuel consumers[213].

Biomass gasification has been given specific relevance in the recent years as one of the avenues of improved energy recovery. The generation of electricity through gasification of vegetable biomass is discussed, which is greenhouse waste[214]. In line with this, various gasifier design and analysis models have been created and these are the thermodynamic equilibrium, kinetic and artificial neural network (ANN) based simulation and optimization models [215]. Heat, electricity, and transport energy can be generated using the combustion engines to convert biogas generated by fermentation of solid and liquid biomass [216, 217]. To evaluate the performance of different agricultural biogas plants on the economic, environmental, and social aspects of evaluation through corresponding indicators, chose to perform a multi-criteria assessment of biogas plants[218].

Geothermal Energy

Geothermal energy means the thermal energy that is stored on the earth. Geothermal heat pumps are among the most commonly used applications of it and it is one of the most effective renewable energy technologies in space heating and cooling. Their operation takes advantage of the comparatively constant subsurface temperature at the depth that is usually warmer than the ambient temperature during winter, and cooler during summer. The major benefit of geothermal resources is that they can provide 24-hour supply of energy, and not the intermittency of other renewable sources like wind and solar. Even though geothermal power plants tend to be capital intense in the initial investment, the overall costs of operation are usually low thus allowing the generation of energy at competitive costs at appropriate locations. Plants using geothermal power are already being used in 19 countries, with more being commissioned (such as in Indonesia, Italy, Turkey and United States in 2009). However, very little of the world geothermal potential has been exploited so far meaning that there are enormous potentials of speedy implementation in the generation of electricity and in direct-use. Geothermal energy is capable of providing significant contribution towards the mitigation of greenhouse-gases due to its technical maturity and a large base of resources [219]. It has been found to be advantageous especially in arid areas where freshwater remains the most important resource in supporting human settlements; in these situations, geothermal resources are not only important in offering energy services but also in heating green houses and provision of fresh water [220].

Geothermal heat pumps are used in the construction of buildings to carry the heat present in the ground to the inside rooms when there is need to heat them during winter seasons and reject heat to the ground during summer seasons. The main element of these systems is heating exchangers, and its functioning relies on various design and operating parameters, out of which heat-transfer area has a significant impact. An optimization method was suggested to arrive at settings of heat-exchangers which would maximize the net profit in a year [79, 221, 222]. In the case of low-enthalpy geothermal aquifers, a genetic algorithm (GA) is used to optimize the design of the

exploitation system by ensuring that annual pumping costs are minimized and that the amortization costs of the network of pipes which carry the hot water to the production wells to a centralized storage tank at field boundary are also taken into account[223]. Their results show that the suggested methodology helps the enhanced planning and more affordable implementation of low-enthalpy geothermal heating units[224].

3.4. Hybrid System

The top ranked compounds from the machine the above sections have outlined the major challenges that are presented by the major renewable energy resources. The weakness that results in a constant limitation is the variability of generation, which may compromise the reliability of the operation and complicate the process of planning the system[225]. As an illustration, commercial systems of stand-alone street-lights, using the traditional photovoltaic-battery arrangement, might not work throughout the year at areas well north or south of the equator, due to seasonal limitations in the solar-sunshine quantity [226]. As a result, further research and developments of solar and wind and other renewable technologies are needed to maximize performance, better predictability, and reliability when combined with other forms of conventional generation [227].

Table 3. Representative optimization studies for hybrid renewable energy systems

Study (as cited)	Hybrid system type	Objective(s)	Method	Key note
El Haj Assad et al. [225]	Hybrid system (general)	Min energy cost + min lifetime GHG	Multi-objective algorithm	Cost–emissions trade-off
Garg, H et al. [119]	Economic dispatch	Solve nonconvex dispatch	PSO	Better than conventional methods
Capik, -Llácer-Iglesias, et al. [184,185]	Isolated hybrid PV–wind–diesel	Min life-cycle cost + emissions (+ unmet load)	MOEA/SPEA	Practical sizing framework
Sipahutar et al. [186]	Solar–wind–battery	Min annualized cost + min LPSP	Multi-objective GA	Reliability-constrained sizing
Luis et al. [187]	Solar–wind–battery	Min annualized cost + min LPSP	Pareto-based GA	Pareto sizing
Welch, J.B et al. [86]	Wind–PV for industrial TOU	Max investment benefit	PSO	Capacity coordination

Study (as cited)	Hybrid system type	Objective(s)	Method	Key note
Adhikari et al. [191]	Wind–PV–fuel cell	Min annual cost subject to reliability	PSO	Reliability-focused sizing
Cornelissen et al. [201]	PV–wind stand-alone	Min cost with full load coverage	GA	Unit selection & sizing
Singh et al. [202]	Solar–wind + batteries	Optimize PV, wind, battery + tilt/height	GA	Design variables expanded
Jain et al. [208]	Pico-hydro + wind + PV + diesel	Min cost + reduce excess energy	Optimization method	Shows value of modeling surplus

During the last ten years, there has been a significant growth in the desire to design and operate standalone hybrid power generation systems optimally due to the necessity to balance captured renewable energy and demand, and ensuring reliability and minimizing cost [228]. Properly sized and managed hybrid systems might be the more cost-effective and reliable in their provision than single-source renewable systems, and with growing interest in the technical and economic aspects by which they warrant implementation [229]. Several multi-objective optimization methods have been suggested to maximize the renewable mix, or the combination of renewable with other generation sources, in terms of contribution to peak demand, aggregate intermittency, and cost targets [60]. As an example, a multi-objective formulation came up with a multi-objective formulation that is used to reduce the energy cost and at the same time lifetime greenhouse-gas emission that is used to reduce the energy cost and at the same time lifetime greenhouse-gas emission [230]. Broadly, economic dispatch in the contemporary power systems is defined by nonlinear, non-convex objective functions and strict equality and inequality constraints, where classical methods of optimization may fail since it is usually entangled in local-optimum problems. As illustrated, particle swarm optimization (PSO) is able to mitigate these challenges and claimed a high level of performance as compared to the traditional techniques[54, 231]. Likewise, a multi-objective evolutionary algorithm (MOEA) was utilized to solve the economical-environmental dispatch problem of a hybrid system with wind and solar thermal generation in order to reduce the cost of fuel and the emissions of pollutant to the environment; the use of genetic algorithms (GA) has also been common in optimization of economical load dispatch of systems with wind integration[232]. The design of isolated hybrid systems was optimized with multi-objectives (minimization of life-cycle cost and emissions), using Strength Pareto Evolutionary Algorithm (SPEA); their example of photovoltaic-wind-diesel showed the practical nature of the engine[233]. They then built this model to three-objective formulation that further adds unmet load as a measure of reliability [234]. Such sizing works as those who considered a multi-objective GA to the solar-wind-battery system with a minimization of annualized cost and probability of power loss and [236] who designed a Pareto-based GA with analogous goals [235]. Montoya et al. introduced Pareto-based metaheuristic between PAES and simulated annealing and that minimizes the voltage variations and power losses in the power networks which can be modified to apply to hybrid-systems.

Remote-area electrification has gained more and more relevance through the development of hybrid renewable energy systems, which provide possibilities to use renewable technologies and energy storage. The approaches of optimization used to develop supervisory and operational strategies include linear programming (LP) and fuzzy logic [237]. However, the uncertainty in the availability of renewable resources, the demand of loads, the nonlinearity of important components makes the design of the hybrid-system intrinsically difficult. Additionally, the criteria of evaluation are usually represented at both economic and environmental levels that are usually conflicting, which supports the aspects of multi-criteria and multi-objective optimization. To this end, several studies have been conducted on the topic of selecting an optimal mix of renewable technologies with consideration of the resource profiles, technology properties, policy incentives, and cost parameters (e.g., installation and maintenance). PSO was used to manage wind-photovoltaic capacity in coordination with an industrial user in the time-of-use price so as to maximize investment returns [238, 239]. PSO was also applied to optimize wind-photovoltaic-fuel cell hybrid system to reduce the annual cost under reliability constraints[240]. A photovoltaic-battery-fuel cell system with the combination of GA and simplex optimization was used to fit a stand-alone street lighting [241]. An optimization method of wind-photovoltaic systems was offered with the help of monthly averages of solar radiation and the wind-speed [242]. An optimization framework of a complex hybrid architecture of photovoltaics, wind generators, storage, electrolysis, hydrogen tanks, compression, fuel cells and diesel backup was also offered[243].

To electrify remote communities that are infeasible to be connected to the grid, isolated hybrid systems (e.g. wind, solar, micro-hydro) with storage can also be viable [244]. Surveys of battery storage in hybrid systems optimization strategies were reviewed by [245], simulation and optimization control technologies of standalone solar wind systems with batteries were surveyed by [246], where the variety of methods of predicting and reliable integration is emphasized. GA was used in other instances to work out optimal settings of islanded systems of diesel generators, wind turbines, photovoltaics, and batteries, [247] and suggested a multi-source hybrid (biomass, wind, solar PV, battery) to maintain peak-load delivery under low-resource settings [209]. The design, operation, and control requirements of standalone photovoltaic wind systems with traditional backup outlining possible research in future was also explored[248].

Back-end planning of the hybrid-system demands simultaneous attention to component dimensioning as well as control policy. The size and schedule of units in the wind-diesel system with hydrogen storage were examined by applying hourly time-series wind and demand data with the use of LP and fixed dispatch. A GA was designed to select the optimal sizing of stand-alone photovoltaic-wind system and choose the type and quantity of units to minimize the cost when the full load should be covered[249] [250]. GA-based sizing was expanded to incorporate the decision variables, like PV module tilt and the turbine hub height [251]. A method of sizing a wind-battery system using intermediate hydrogen storage using actual wind records and load demands of residential users was also outlined[252]. An evolutionary algorithm of the combined design and control of photovoltaic-wind-diesel-battery-hydrogen system, and indicated high-quality solutions using a small amount of computation. A photovoltaic-based electrolyzers-metal hydride-fuel cell system was evaluated, and observed that this system exhibited better operational benefits compared to PV-only systems, but that system operation optimization is a complicated process[253]. The sizing of stand-alone PV-wind systems to be autonomous at minimum leveled

cost was examined[254]. PSO can reduce total costs in fuel-cell-based hybrid systems with wind, electrolyzers, reforming, anaerobic reactors, and hydrogen tanks and meet residential demand limitations [255].

In addition to size and cost, renewable penetration has an impact on the larger power-system operation. A hybrid Pico-hydro, wind, solar PV, and diesel generation system was optimized, where excess generation is minimized and cost minimized showed that express focus on surplus generation can lead to cost reduction. Uncertainty Planning Uncertainty planning has also been discussed in thermal units combined with wind and solar with the use of GA and PSO[256]. A day-ahead operating approach of a multi-reservoir hydropower system was suggested that is synchronized with wind and has a common transmission system[257]. An optimization strategy of daily operational scheduling relating to the wind turbines and hydro pumping equipment was also developed[258]. Control oriented works, who created a neuro-fuzzy controller in wind diesel system found that it performed better than the fixed-parameter fuzzy logic and PID controllers[259, 260]. GA was used to the control and design of a photovoltaic-diesel hybrid system. Another possible direction has been hybrid wind hydro generation to enhance wind penetration in isolated grids[261]. An in-depth operational simulation with an evolutionary optimization were also coupled to scale reversible hydraulic-system components and financial parameters [262]. A two-loop solar-plus-fuel boiler system was also simulated to boost the ability of hot-water loads replacement and boost the thermal efficiency of the solar subsystem[263].

Review Methodology

The aim of the given review was to summarize the latest advances in computational optimization approaches the renewable and sustainable energy systems, specifically focusing on optimization issues in the fields of design, planning, and control. The scope also includes significant renewable technologies that are addressed in this manuscript (e.g. wind, solar, hydropower, bioenergy, geothermal, and hybrid designs), and also stresses classical methodologies of optimization as well as newer methods of heuristic/metaheuristic optimization. In order to be consistent with the analysis given in the manuscript (e.g., the publication trend and country distribution), the review targets the publications published within 20-year-span, and specifically the peer-reviewed research articles with definite optimization formulation and an explicit application to a renewable or sustainable energy problem.

Literature was gathered by means of systematic search of big scholarly indexing databases and publisher databases of literature utilized in research of energy and engineering topics (e.g., Web of Science/ISI Web of Knowledge, Scopus, and large digital libraries like IEEE Explore and ScienceDirect with relevant keywords), using combinations of keywords of both, the area of application and the optimization methods. Common search terms were renewable-energy terms with terms that optimize (e.g. optimization, optimal design, planning, control, dispatch, sizing, siting, economic dispatch) and algorithm terms (e.g. linear programming, mixed-integer, genetic algorithm, particle swarm optimization, evolutionary algorithm, multi-objective, Pareto). Records were filtered to eliminate duplicates and items out of scope, and review articles were explicitly filtered to make sure that Fig. 1 reflects the output of primary research. The rest of the papers were screened by title/abstract screening, and then full-text screening, as papers that explicitly use an optimization algorithm to a renewable-energy design/planning/control problem were retained. The main information of each of the included studies was then identified in a standard template (energy source, problem type, decision variables, objectives like cost/emissions/reliability, constraints, optimization technique, and reported results). The resulting metadata were

subsequently summarized to generate the descriptive statistics of the manuscript, such as the yearly publication trend (Fig. 1) and the scheme by country according to author affiliation metadata (Fig. 2), and thus allowing these numbers to be traced back to the screened literature set.

4. Research Gaps and Future Directions

Literature reviewed reveals a booming trend in application of optimization in the renewable-energy especially wind energy and solar systems, in addition to the expansion of the use of metaheuristics (especially GA and PSO) and Pareto-based multi-objective frameworks in addressing conflicting goals. Although these developments have taken place, a number of gaps exist that restrict scalability, comparability, and the practical implementation. The parallel and accelerated optimization that is one of the most noticeable opportunities, since most optimization problems in the field of renewable energy have large search space, nonlinear constraints, and multidimensional decision variables, but parallel processing and high-performance computing is relatively underrepresented in much of the literature. Paralleled metaheuristics, distributed evaluation of candidate solutions and combinations of exact solvers with heuristics can be used in future studies to enhance both the computational efficiency and solution quality in finding solutions to realistic system models.

The other direction of critical concern is uncertainty-aware optimization, since renewable generation and demand process are complex as they are variable in nature, and subject to forecasting error. Although deterministic formulations are still in common use, stochastic, robust and chance-constrained formulations should be used more frequently to guarantee reliability in uncertain conditions and to generate designs and dispatch strategies that could be viable in a dynamic environment. Similarly, there are opportunities to deepen the research in the design and functioning of hybrid systems with storage under the climate variability and seasonal patterns, as the system size and control, which are effective in the case of average conditions, could fail in cases of the long-term low-resource conditions or even extreme phenomena. Besides, despite the growing popularity of multi-objective optimization, more research is necessary to enhance the decision support in final design selection among the Pareto sets, especially practical trade-offs between cost, emissions, and reliability, as well as to include the preferences of stakeholders and policy constraints transparently.

Lastly, high reproducibility and benchmarking would add a lot of value to the field. A lot of studies vary in datasets, assumptions, performance measures, and reporting format and thus it is not easy to compare just one algorithm with another. In the future, it is important to focus on standardized test systems, open datasets (resource and load profiles), properly defined reliability indices, and periodic reporting of objective functions and constraints, preferably with publicly available code and parameter settings. Such measures would enable the community to justify findings, cross procedures on similar grounds, and hasten the process of getting to the optimization schemes that are scientifically sound and practically implementable in achieving renewable and sustainable energy systems.

5. Conclusion

In this paper, the current advancements in the implementation of optimization methods in the design, planning, and control of renewable and sustainable energy systems are reviewed. The review, surveying over two hundred

articles published by major peer-reviewed journals in the field of renewable energy and computational optimization, illustrates the key trends in research and provides the concise findings, which could be utilized by the researcher working in the corresponding field. The evident outcome of the literature is the drastic increase in the number of studies implementing optimization to renewable-energy issues, with wind and solar applications exhibiting a significant growth. The methods reviewed include classical mathematical programming, traditional optimization methods, including mixed-integer and interval linear programming, Lagrangian relaxation, quadratic programming, and the Nelder-Mead simplex method, and the increasingly popular heuristic and metaheuristic methods, in particular, genetic algorithms and particle swarm optimization. Meanwhile, Pareto-based models of multi-objective models have become a common subject of discussion due to the necessity to address cost-reliability-environmental trade-offs. Parallel processing, conversely, has not been utilized relatively as extensively in this literature.

In general, heuristic optimization, the Pareto-based multi-objective optimization, and the parallel computing are presumably some of the best prospects in the prospective study of renewable and sustainable energy optimization.

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