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Application of Artificial Intelligence Methods for Hybrid Energy System Optimization

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ABSTRACT

Consciousness of the need to decrease our unnatural weather changes and of the critical increase in the costs of traditional sources of energy have motivated many nations to provide innovative energy strategies that promulgate renewable energy systems. For example, solar, wind and hydro related energies are renewable energy sources, and they are environmentally friendly with the potential for broad use. All of the load requirement conditions in comparison with single usage can provide more economical and dependable electricity, as well as environmentally friendly sources, by compounding such renewable energy sources using backup units to shape a hybrid scheme. Sizing the hybrid system elements optimally is one of the most important matters in this type of hybrid system, which could sufficiently meet all of the load demands with a minor financial investment. Although a number of studies have been performed on the optimization and sizing of hybrid renewable energy systems, this study presents a full analysis of Artificial Intelligence optimum plans in the literature, making the contribution of penetrating extensively the renewable energy aspects for improving the functioning of the systems economically.

Contents

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1. Introduction

One of the prominent challenges that the world faces today is providing its needed energy while saving for the future simultaneously [1]. In recent times, a considerable amount of energy has been required around the world. The world depends solely on conventional energy sources, for example, coal, natural gas and crude oil [2,3]. In addition, the demand for energy use is growing every day, which, however, results in a brisk demand for the usual fossil fuels [4,5]. Whereas these sources of energy are limited and unload quickly, that in turn pressures the stability of potential generations of energy demand [6–8]. In addition, the unpredictable supply of the aforementioned sources and the negative influence on the administrative balances between energy (petroleum) exporting/importing nations warrants vital investigations on the prospects of popular means for producing energy [9]. In recent years, global warming and climate change are two main important issues in the global economy and environment, and they have a considerable effect on the insufficient accessibility and rising cost of energy [10]. The high consumption of energy in the world has already increased concerns about supply difficulties and significant environmental influences, such as global warming and climate change [11–13]. The evidence from [7,14–17] concludes that energy created by traditional energy sources causes an increase in greenhouse gas discharge, which could affect global warming. Efforts to reduce the volume of greenhouse gas emission have led to the Kyoto agreement on the global decline of greenhouse gas production. This agreement was put in place to lessen the issue and the dependence on traditional energy systems. The notion of greenhouse gas reduction is valid for both developing and developed nations [18,19]. Addressing the issues discussed above, continual potential action for sustainable improvement is required. In addition, cost-effective, consistent, and environmentally friendly energy systems are the attributes of a sustainable energy system that efficiently uses local assets and networks [20]. Therefore, renewable energy sources are positioned as one of the proficient and useful solutions [7,15]. There are different types of renewable energy structures, such as wind, solar, hydro-electric, water, ocean, biomass and geothermal energy, which have unique benefits and are suitable for applications. Currently, some countries have the potential for different types of energy resources, such as solar, wind, water, and geothermal, and in addition, many companies are developing, constructing and setting up modern and high-tech renewable energy systems. These countries attempt to lead a large network of investigators and other partners to utilize cutting-edge and advanced technologies that will provide a cost for renewable electricity generation that is competitive with traditional sources of energy. Increasing the proportions of renewable energy systems such as wind and solar have joined the grid and will impact the fossil fuel generators on the grid, which will lead to a decrease in emissions and costs for the consumers. These advantages include, for example, a reduction in the external energy confidence and a decrease in communication and conversion costs. Additionally, renewable energy sources supply an important improvement over the usual energy systems, and almost none discharge gaseous or water pollutants during their operations [20,21]. As mentioned before in this study, renewable energy systems are measured as capable power producing sources. On the other hand, a disadvantage of the specified energy selection is their irregular character and our confidence in the weather conditions. Therefore, renewable power production cannot completely control the power requirement of the load at any specific instant in time [14,22–24]. This type of difficulty is connected to the changeable character of these resources, which can be solved by assimilating resources in an appropriate hybrid blend. This approach causes an improvement in the system's effectiveness and reliability of the energy supply [7,14,25]. As a result, renewable energy access can be improved in upcoming sustainable areas [13]. Renewable energy systems present some helpful effects in several types of applications modes, which have been identified to be, for example, the costs of the systems when preventing wide-ranging consumption, assessment efforts that are focused on fast cost falls, and the ability of these systems in development [4]. Method designs should be most favorable in operations and component selection, to achieve electrical energy from renewable energy resources, which is related to hybrid system reliability and cost efficiency [26–28]. Therefore, the most advantageous sizing method is to proficiently and inexpensively use renewable energy resources [9]. Principally, the most favorable size systems are required for comprehensive analysis to give the location and control site-dependent factors, such as solar rays, wind rates, and temperatures, and their costs [14,29]. Computer-based simulation and optimization has become a preeminent technique for designing power systems; this approach involves comprehensive analysis [30]. There are some constraints in the formulation and solution of the design and optimization approach, such as the resource availability, technology, efficiency, mathematical models and other aspects. However, the advancement in computational techniques has made it easy to address optimization problems by using a number of optimization and simulation techniques. A number of simulation tools, such as HOMER (Hybrid Optimization Model of Electric Renewable), HYBRID2 (The Hybrid Power System Simulation Model), and HOGA (Hybrid Optimization using Genetic Algorithm), are used for the design and optimization of hybrid systems as well as for improving their performance. One of the main branches of computer science is Artificial Intelligence (AI), which investigates and builds intelligent software and machines. Russell and Norvig [31] explain that AI is “the investigate and framework of intelligent factors”, in which an intelligent factor performs actions that maximize the possibility of success. AI is composed of branches such as genetic algorithms (GA), particle swarm optimization (PSO), simulated annealing (SA), artificial neural networks (ANN) and hybrid models, including two or more previous branches. The effective and correct application of intelligent methods cause the development of comprehensive and useful systems with better performance or different characteristics, which cannot be obtained compared to using traditional approaches [32]. This paper aims at reviewing the literature that is related to the various optimization techniques of Artificial Intelligence Methods for Hybrid Energy Systems Optimization, such as genetic algorithms (GAs), simulated annealing (SA), and particle swarm optimization (PSO). In addition, the characteristics of all of the methods are compared together, to help researchers to use them effectively and in a cost-effective manner.

2. World energy scenario

According to the Energy Information Administration, the global energy consumption is increasing by approximately 2.3% per annum [33]. The wind generates approximately 20% of the electricity in Denmark. However, on a global scale, the electricity that is produced from the wind is less than 1%. The statistics of world energy consumption from the year 2008–2035 is expected to grow by approximately 53% [33]. Fig. 1 exhibits the high development of the universal energy requirement.

Fig. 2 shows the United State's electricity generation from fuel during the years 1990–2040. Additionally, it shows that the renewable share would be increased by a few percent; however, some sources, such as fossil fuels comprising coal and natural gas, are still increasing.

The world's economic development is surprisingly dependent

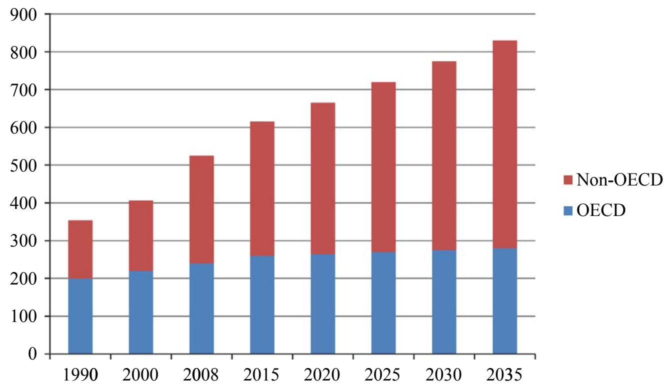

Fig. 1. World energy consumption, 1990–2035 (quadrillion Btu).

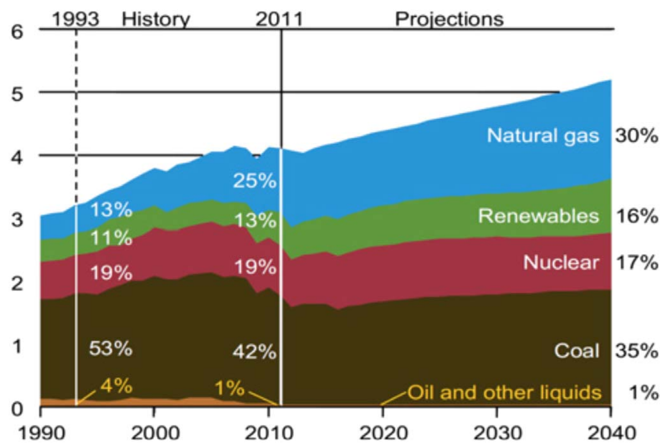

Fig. 2. US electricity generation by fuel, 1990–2040 (trillion kilowatt-h per year) [34].

on increasing energy requirements. In addition, fossil fuels are not consistently spread around the globe, and if the world economy depends heavily on them, local or global disagreement could occur and create an energy crisis. The use of today's predictable combustibles, the worldwide surroundings and the situations of some countries have been unfavorably impacted. We must emphasize that it is important to discover new actions to connect suitable quantities of energy [35–38]. Fig. 3 demonstrates the energy production in the US according to different sources. In the years 2011 and 2012, there is increased global demand for renewable sources of energy supplied at 19% of the global energy usage in the year 2011.

3. Literature review

The design of hybrid renewable energy systems is a significant area, and many researchers are interested in this topic. Therefore, there is a large amount of literature on this topic, which we can use. The design problem mentioned above is related to the energy systems that are observed to have the optimal pattern and optimal location, type and sizing of generation components established on individual nodes. Therefore, this type of system can load the requirements with a minimum of costs [39]. The proposal of hybrid renewable energy can estimate the cost and production over a lifetime of this technology. The first estimate, for the lifetime cost, usually includes two components: the operational cost, such as the principal cost and the preservation cost, which both point to a "fixed cost". Additionally, in a computation of the life span cost, the financial values are modified according to the timing and should be considered. Therefore, the optimized hybrid system patterns combine producer types and sizes in the minimum life span cost and production. Thus, the design by the lowest "Net Present Value" (or NPV) is defined as the "optimal configuration" or "optimal design", with all probable hybrid system designs being in optimal transition [40,41].

There are many methods for providing an "optimal design" indicator and many software tools that are accessible commercially, to act as real-time system integration. Additionally, there are different optimal techniques that are applied from many researchers to use for hybrid renewable energy system sizing. Different Optimization methods, such as graphical construction [42,43], probabilistic techniques [44], iterative approach, dynamic programming, artificial intelligence (AI), linear programming [45,46] and multi-objective were implemented by investigators to optimize hybrid PV/wind energy systems. Table 1 presents a summary of the optimization methods that were developed by different researchers.

3.1. *Commercially existing software applications for the sizing of Hybrid Systems*

Various existing software applications of Hybrid Energy

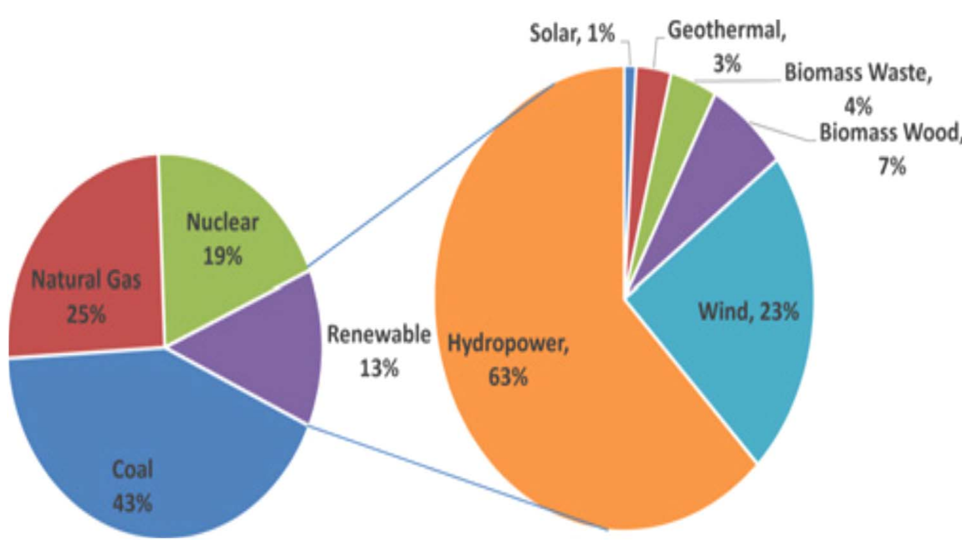

Fig. 3. Energy sources in the US [35].

Table 1
Different optimization methods.

Optimization methods	Optimized factors	Notice
Artificial Intelligence a. Genetic Algorithm b. Particle Swarm c. Simulated annealing d. Artificial Neural Network e. Hybrid model	Hybrid solar-wind system with battery bank	Using Evolution approach
Iterative Method a. Hill climbing b. Dynamic Programming c. Linear Programming d. Multiobjective	Hybrid solar-wind system	Using LPSP to determine different conditions of solar-wind combination
Graphical Construction	Battery and PV array	Usually applied for two factors
Probabilistic methods	Efficiency of hybrid system	By using statistical method of data gathering
Deterministic methods	Standalone PV with battery bank	Based on equations applied for finding particular values when applying fixed factors
Software based a. HOMER		Using an input file with all of the essential data based on a software application

Table 2
Summary of software tools for designing an HES.

Number	Software	Input	Output
1	HOMER	• Load command • Source input • element details, such as capital, maintenance and replacement expenses • System control	• improve unit sizing • Energy and net cost. • Small part of renewable energy
2	HYBRID2	• Load demand • Resources input • primary investment and O&M components cost Components details	• Unit sizing with cost optimization • expenses of energy • Release proportions of the different greenhouse gases • System payback periods
3	HYBRIDS	• Solar size • Turbine type of wind • number and type of battery	• Cost • Percentage of greenhouse gases
4	RET Screen	• Information loading • Solar size • Necessary hydrology and invention database • Climate database	• Energy release and store • Costs • Production decreases • Economic capability • Risk analysis
5	TRNSYS	• Meteorological data input • Ingrained models	• Dynamic simulation of electrical energy sources
6	IHOGA	• Data loading • Resources key input data • Elements and economics facts	• Multi aim improving • charge of energy • Life cycle release • study for addressing energy

Systems (HES) are discussed in this paper. Among them, HOMER plays a significant role in applications of HES, which involves quickly searching for the optimal sizing of the energy systems. Additionally, it is useful to analyze the sensitivity of investigating the influence of uncertainty or changing factors. A list of this software for the design of an HES is presented in Table 2.

3.2. Artificial Intelligence Methods in support of Hybrid Energy Systems Optimization

3.2.1. Genetic Algorithms (GA)

One of the optimization methods operates in terms of the genetic process for biological mechanisms and is called GAs, which have the ability to present a problem-solving method for difficult real-world problems [47,48]. Holland first represented the concept of GAs [49], and afterward, it was widely utilized in many applications, case studies, and information mining. There many published articles that regard GA usage in hybrid systems, for research on sizing. For example, Yang et al. [50,51] and Bilal et al. [52] make use of GAs for a PV hybrid wind system, to perform sizing. Koutroulis et al. [53,54] used genetic algorithms to find the energy expenses of the whole system and confirmed that the application of hybrid PV/wind systems can lead to lower expenses of the systems in comparison with systems in which the sources of exclusively PV and WG are applied. On the other hand, Lagorse et al. [55] used GAs in designing a multi-source hybrid source that combined wind and oil. Examples of PVs are wind, oil, microturbines, and a battery, which had improved sizes according to Kalantar et al. [56], from their use of Genetic algorithms. Additionally, Lopez et al. [57,58] programmed Hybrid Optimizations based on Genetic Algorithms (HOGA), as a simulation application to plan compounds of stand-alone hybrid energy systems with content from renewable sources and typical diesel generators. Lagorse et al. used a hybrid GA and simplex-based method [59], and Zhao et al. [60] planned a GA that includes a wind source and fundamental technical specifications as the main elements. These were used as input parameters. Additionally, a wind source for the energy has been established to reduce the production cost and improve the system's reliability. Additionally, Li et al. [61] improved the rate of gearbox proportioning by using a GA; in so doing, the power ratings of the multi-hybrid stable wind generators improved. On the other hand, the wind outline for maximizing energy production includes the positions for the wind turbines on the land [62]. Grady et al. [63] offered a GA to conclude the optimal generation of wind turbines with the highest production capacity while restricting the number of turbines that were fixed and the area of the land that was filled by each wind farm. Emami and Noghreh [64] used a new coding approach and a novel objective function with GAs to solve this problem. Their method performed better than previous methods that were proposed for the management of the cost, power and effectiveness of the wind farm. Li et al. [65] used a multi-level GA and could solve optimal design problems as well as active control algorithms for the wind. Additionally, Kalogirou [66] solved financial goals in increasing the system of solar energy by implementing ANNs and GAs. The ANN method is suitable for making the connection of the collector region and high container size using the minor power that is desirable for the system. Then, a GA is applied to calculate approximately the best size of the factors to lengthen the life-cycle reserves. Varun [67] used the GA method to increase the thermal execution of flat laminate solar air warmers by reflecting several systems and operating factors. Last, the GA approach was used by Zagrouba et al. [68] to determine the electrical factors. This study involves photovoltaic solar cells and modules for the determination of the analogous highest power point.

3.2.2. Particle Swarm Optimization (PSO)

One of the improvement techniques, which involves shifting and swarm intelligence based on evolutionary calculation techniques, is the PSO. This method was implemented by James Kennedy and Russell Eberhart in 1995. A component of the swarm is the system model or social constitution of a basic person to make a group that has some intention, such as food searching [69,70]. In comparison with GA-based methods, there is some similarity between them. The entry data of the PSO approach includes meteorological circumstances, the unit cost of the hybrid components such as installation and continuation costs, limitations and appropriateness of purpose and the principles of specific PSO factors. One of the population-based optimization procedures is the PSO-based sizing methodology process. PSO has a large amount of use in hybrid sizing research, such as with GAs, and finding literature examples, such as Gas, is not difficult. Researchers such as Sanchez et al. [71], Dehghan et al. [72] and Kaviani et al. [73] planned a unit sizing PSO system to PV (wind and oil) unit microgrids, and a wind and fuel (oil) cell configuration was recognized by Tafreshi and Hakimi [74,75]. On the other hand, a wind–PV hybridization and PSO were planned with Wang and Singh [76] and Zhao et al. [77]. The same study shows that Wang and Singh [78] employed a PSO in network equivalent hybrid renewable energy systems. For handling hybrid systems, a multi-criteria approach was proposed to solve hybrid systems such as wind turbine generators of wind turbines, photovoltaic panels, and battery problems. These problems have multiple design objectives, such as costs, consistency and releases [79]. There were more than 20 varieties in the proposals that used PSO algorithms. Zhao et al. [80] used Hybrid Particle Swarm Optimization and Wavelet Mutation (HPSOWM) along with GAs. HPSOWM performs efficiently and fast. The Binary Particle Swarm optimization (BPSO) algorithm was also introduced by Kennedy and Eberhart. This approach enables the use of PSO for binary problems [80]. Pourmousavi et al. [81] claimed that particle swarm optimization (PSO) has a very rapid convergence time in comparison with sequential quadratic programming optimization in terms of the energy management. Additionally, forecasting the wind speed is indispensable in wind-related engineering studies and is important in the management of wind farms. As a technique that is essential for the future of clean energy systems, reducing the forecasting errors that are related to the wind speed has always been an important research subject. In this paper, an optimized hybrid method based on the Autoregressive Integrated Moving Average (ARIMA) and Kalman filter is proposed to forecast the daily mean wind speed in western China. This approach employs Particle Swarm Optimization (PSO) to find the optimum factors of the ARIMA model, which develops a hybrid model that is best adapted to the data set, increasing the fitting accuracy and avoiding over-fitting. Afterward, the suggested method is tested on the wind farms of western China, where the proposed hybrid model is shown to perform effectively and steadily [82]. A model for a wind-CAES system was developed by Kahrobaee and Asgarpoor [83] to optimize the daily activities and long-term plans of systems that use the PSO algorithm to maximize their profits. In addition, particle swarm optimization (PSO) was applied to find the maximum placement and sizing of PV distributed generation in radial distribution systems to decrease the power loss. The final result shows that PSOs can achieve a maximum power loss decrease [84]. In another investigation, a novel method is suggested to find the optimum design of hybrid renewable energy systems that are composed of different generators and storage devices. The ε-constraint approach has been used for minimizing simultaneously the total cost of the system, the fuel emissions and the unmet load. A particle swarm optimization (PSO)-simulation based method has been applied to address the multi-objective optimization problem. Finally, sensitivity analysis was performed for investigating the sensibility of different factors to the constructed model [85].

3.2.3. Simulated Annealing (SA)

Studies about wind PV batteries and renewable hydrogen hybrids used the Simulated Annealing (SA) method on optimization problems through a simulated annealing process [86]. By the ability to avoid local minima, it can integrate a possible role for accepting or rejecting new problem-solving methods. This method was established by Kirkpatrick, Gelatt, and Vecchi in 1983 [87], and it has been implemented and expanded since the 1980s′ simple architecture, with effective contributions [88]. The early heating and cooling processes are important to the SA. The basic algorithm's criteria are the setting value, deviation, cooling plan, and acceptance of search execution. Simulated annealing in ARENA 12.0 software was used by Ekren et al. [25] to find the optimum point of performance of a hybrid system by considering the loss of the load probability and autonomy analysis on an hourly basis. According to Sutthibun and Bhasaputra [89], the model that was used to identify the optimal location and size of the DRG to minimize the real power loss (PL), production (Epg), and the possible severity index (SI) that it faced with regard to apower balance and power generation limitation, used SA as an optimization tool. Based on Ghadimi and Ghadimi [90] in 2012, SA minimized the power losses for sizing the DRG and storage banks in a distributed network. According to Fungetal [91], to obtain the generator settings and battery charge or discharge schedules in everyday loads, SA was used in a diesel generator and a sine wave inverter with a controller element. Katsigiannis et al. compared SAs with the Tabu algorithm for sizing in an HRES that was used to minimize the COE. As a result, SA was faster to converge, although it was less efficient than the other method [92].

3.2.4. Hybrid models

Hybrid approaches are a useful collaboration of two or more different methods that use the beneficial effects of the methods in achieving an optimum result for a particular design problem. Because most of the difficulties that we tackle are multi-objective, conducting a hybrid method is an excellent objective in nature, and utilizing a hybrid approach is a suitable alternative method to address problems that require considerable comprehension of all of the methods. Meza et al. [93] developed a multi-objective model to generate expansion planning (MGEP) and an analytical hierarchy process (AHP) model to address a multi-objective problem that included costs, environmental effects, fuel price risks and imported fuel. One solution was achieved by Nasiraghdam and Jadid [94], by using a multi-objective artificial bee colony (ABC) algorithm that had considerable quality and good diversity of the pareto front in comparison with multi-objective PSO (MOPSO) methods and non-dominated shorting GA-II (NSGA-II). Alsayed et al. [95] used different multi-criteria decision analysis (MCDA) optimization techniques to determine the optimum sizing of PV–WT. Sensitivity analysis of MCDA algorithms was performed by accounting for different weighting criteria approaches with different types of vacillation scenarios of solar radiation and wind speed. Although it was complex, beneficial results were provided that were helpful in the design of hybrid energy systems. An Artificial Neural Network (ANN) strategy was used by considering flow batteries to control the uncertainties in the wind outcomes based on the further lower energy costs. Table 3 shows a brief summary of additional hybrid methods in more detail.

3.3. Promising method in Hybrid System sizing for future use

3.3.1. Algorithm of ant colony

Finding the direct path of the ants is a developmental routine that has recently been recognized. The basic Ant Colony algorithms were established on the recital of social creatures that have the ability to look for the fastest paths to the food sources while applying famous mater as a pheromone [100]. The pheromones are the chemical objects that are reserved by the ants to form a communication media among them. Ant Colony System Algorithm (ACSA) is the addition of Ant Colony Optimization (ACO). In most engineering applications, it has better action than the ACO [101–

Table 3
Summary of Hybrid models.

Reference	Systems studied	Topics covered	Highlights
[93]	Oil/steam, coal/seam, , hydro, wind, nuclear	Total costs, CO2 emission, Fuel consumption, Energy price risk and minimization of outage cost (reliability)	• The research indicates a multi-objective generation expansion planning (MGEP) model of a power electric system that involves renewable energy sources (RES) • The mixed-integer linear programming (MILP) is implemented for the suggested optimization. and an effective linearization approach is suggested to change the non-linear reliability metrics into a set of linear expressions. • Fuzzy decision maker is used to choose the most-preferred solution among the Pareto results.
[94]	PV, Wind and Fuel cell	Power loss minimization, voltage stability index, COE and emissions	• The results that were achieved by the multi-objective artificial Bee colony algorithm have a suitable quality and better diversity of the pareto front compared to the NSGA-II and MOPSO methods.
[95]	PV and wind generator	Emissions decrease, estimated expenses and social acceptance	• This paper includes optimum sizing of PV–WT by using different multi-criteria decision analysis (MCDA) optimization techniques. • Sensitivity analysis of the MCDA algorithms has been performed, in terms of weighting criteria approaches with different fluctuation in the scenarios of wind speed and solar radiation profiles. • The proposed approach gives the decision maker the ability to comprise any type of criteria, enabling a confirmation of the influence of these criteria on the optimal solutions, by considering different input data sensitivity scenarios.
[96]	Costs, environmental effects, imported fuel and fuel price risks	Conventional steam units, coal units, combined cycle modules (CC), nuclear, gas turbines (TG), wind farms, geothermal and hydro units	• In this study, a multi-objective model for a generation expansion planning (MGEP) model is proposed. A model is developed to suggest the nondominated solutions and using the Analytical Hierarchy Process (AHP) to choose the "best solution" among the representative (clustered) solutions. • A large problem is time: access to the main decision makers is restricted, and it could be expensive. Another problem is that there is comparatively limited experience with such approaches in a group setting, in which group members have a variety of priorities.
[97]	PV, Wind, Diesel, Biodiesel and Battery bank	COE and total greenhouse gas emissions (GHG)	• The large sizes of diesel-fueled generators cause COEs that are too small and CO2-eq. emissions that are large because enormous sizes of biodiesel-fueled generators cause a reversal in the outcomes. Moreover, the use of FC with natural gas as a fuel is not suggested because of the enormous expense and the high CO2-eq. emissions that are released.
[98]	Wind generator and battery	Lowest cost of battery connection with large wind farm	• The paper shows sizing and control approaches for a zinc–bromine flow battery-based energy storage system. • The results present that the power flow control strategy does have an important effect on the proper sizing of the rated power and energy of the system. Specifically, ANN control strategies lead to less expended energy in the storage systems than simplified controllers.
[99]	PV, Wind and Battery	Installation expenses and productivity	• This paper assesses the productivity of a hybrid system that includes combinations of renewable energy generation and energy storage to satisfy a controllable HVAC load

104]. Wang et al. improved an optimization process based on ACSA in 2008 by reducing a compound consistency index to determine the best rec-loser and DRG locations. The authors recommended the idea to extend the simultaneous locations of both re-closers and DRGs, which are together dependent on the reliability enhancement [105]. Additionally, Sookananta et al. [106] planned ACSA to find the best location and sizing of the DRG in radial distribution systems, to decrease the general line losses of the net. Other research, such as in Fetanat and Khorasaninejad [107] used ant colony optimization applied to constant domains (ACOR) based digital programming for size optimization in a hybrid photovoltaic (PV)–wind energy system. ACOR is an easy extension of ant colony optimization (ACO). Additionally, it is the notable ant-based algorithm for perpetual optimization. In this setting, the variables are first considered to be real and are then rounded in each step of the iteration. The number of solar panels, wind turbines and batteries are selected as decision variables of the integer programming problem. The main goal of the design of a PV–wind system is the total design cost, which is the sum of the total capital cost and the total maintenance cost; this sum should be minimized. The optimization is separately performed for three renewable energy systems, including hybrid systems, solar stand alone and wind stand alone. A complete data set, a regular optimization formulation and ACOR-based integer programming are the main features of this paper. The optimization results showed that this method gives the best results in only a few seconds. Additionally, the results are compared with other artificial intelligence (AI) approaches and a conventional optimization method. Moreover, the results are very promising and prove that the authors' proposed approach outperforms them in terms of reaching an optimal solution and speed [108].

3.3.2. Algorithm of the Artificial Immune System (AIS)

AISs are motivated by immunology, the role of the immune system and the values viewed in the natural world [109], which was presented in the 1990s. In addition, the immune system is a vital defense against self-approach that protects human health from enemies or pathogens such as microbes and viruses. This

Table 4
Brief summary of Artificial Intelligence Methods for Hybrid Energy Systems.

Reference	Systems studied	Topics covered	Highlights
Solar and Wind Systems			
[113]	Only standalone PV–wind hybrid systems	• Criteria for optimizations and simulation modeling of photovoltaic systems, wind energy systems, battery storage systems • Software tools for hybrid solar–wind system reviewed are • HOMER • HYBRID2 • HOGA	• Artificial intelligence techniques are identified to be promising. which require further exploration
[114]	Study covers PV–battery, PV–wind–battery and PV–wind–diesel–battery hybrid systems	• Optimization Techniques reviewed: • Genetic Algorithms • Honey Bee mating Optimization • Particle Swarm Optimization • Evolutionary Algorithm • Artificial Intelligence • Pareto-based multi-objective optimization and parallel processing	• GA and PSO as the most useful and promising multi-objective optimization methods in hybrid system design
[115]	Study includes standalone and grid-connected PV systems, PV–diesel generator systems, PV–wind systems, PV–wind–diesel generator systems	• Standalone PV systems size optimization methods reviewed are: • Intuitive methods • Numerical methods • Analytical methods • Other methods(Artificial Intelligence) • Reviewed grid connected hybrid systems sizing optimization methods: • Intuitive methods • Numerical methods • Artificial intelligence methods	• Artificial intelligence techniques have the potential to improve the process of optimization
All Types of Hybrid Energy Systems			
[116]	Covers all types of renewable energy-based hybrid systems	• Software tools discussed are: HOMER, HYBRID2, (ORIENTE). (GAMS). The OptQuest, LINDO, WDILOG2, Dividing Rectangles (DIRECT). (SimPhoSys), (DOIRES). (GRHYSO), H2RES and The Geo- Spatial Planner for Energy Investment Strategies. • Optimization techniques discussed are: • Genetic algorithm • Particle swarm optimization • Simulated annealing • Linear programming • Simplex algorithm • Neural Networks • Evolutionary algorithm • Random, repeatable, probabilistic, parametric and numerical way.	• Promising techniques identified are: Ant colony algorithm, Artificial immune system algorithm, Tabu Search, Honey Bee Algorithm, Bacterial Algorithm, Game Theory
[117]	Study includes all types of renewable energy-based hybrid systems	• Reviewed hybrid system performance indicators (Loss of power supply probability (LPSP), Levelized cost of energy (LCE)) • Hybrid energy system sizing methodologies reviewed are: • Probabilistic methods, • Iterative methods, • Hybrid methods (Genetic Algorithm, Artificial Intelligence) • Analytical methods including software or numerical approximations of component	• Study suggests that hybrid optimization methodologies are superior to other methods.
[118]	Covers all types of renewable energy-based hybrid systems	• Discussed design parameters, evaluation criteria and control and energy management of hybrid energy systems _ Software tools reviewed are • HOMER • HOGA • RETScreen • HYBRIDS • TRNSYS • Sizing methodologies reviewed are: • Graphic construction methods • Probabilistic methods • Analytical methods • Iterative methods • Artificial intelligence methods • Hybrid methods	• Hybrid optimization methodologies are recommended for hybrid systems research to avoid the limitations of one methodology

procedure will be able to differentiate among self-cells and non-self-cells. Afterward, the immune system executes an immune answer to remove the non-self-cells [110–112]. Based on the AIS optimization process for hybrid system sizing, the explanations in the search area could be used as encryption in an antigen population in the AIS algorithm. During each iteration, the structure of the antigen populace that was adopted and the peoples' performance through the eradication of impossible solutions were evaluated. Previous antigens, including affinities, were supplanted by new antigens that were beneficial to the collection affinities. A summary of an artificial intelligence application that considers the energy produced based on solar, wind and all types of hybrid energy systems is shown in Table 4.

3.4. Other promising approaches

Many methods can be used as conceptual methods in the future for improving the proficiency and cost-effectiveness in sizing hybrid energy systems. The most utilized methods in applications are the Tabu Search [119,120], honey bee mating algorithm [121,122], bacterial food algorithm [123,124], game playing theory [125,126] and combination of metaheuristic algorithms. In this section, the combination of different methods with artificial intelligence approaches are reviewed based on their energy production, which is produced from, e.g., wind, solar and other hybrid and renewable systems.

3.4.1. Wind systems

Detailed predictions of the wind speed and power are essential for improving the safety of renewable energy utilization. Comparing this goal with physical techniques showed that statistical procedures are usually simpler and produce better fits for small amounts of land. Determined by the designs of wavelets and established time series analysis, a new short-term forecasting approach is proposed. Simulation of real-time data shows that (1) the relative mean deviation in many-step predictions is related to the proposed method by a minute. However, this finding is better than standard time series methodology as well as BP methodology. (2) The suggested method is strong in skipping data. (3) The proposed method applies to both the wind speed and power prediction [127]. Pousinho et al. [128] proposed a stochastic programming method to trade wind energy in a market context under ambiguity. The main reason for the profits obtained by the power producers is the energy market values. The unpredictable nature of wind power shows an additional source of uncertainty.

The wind speed series show uncertain and nonlinear events. The essential and safe use of renewable energy utilization depends on the accurate forecasting of the wind speed. Hybrid models always have tremendous accuracy. According to the theories of Wavelets, particle swarm optimization, artificial neural networks, and genetic algorithms, two hybrid predicting frameworks "(GA) and (PSO)" are suggested to predict the non-fixed wind rates. Comparisons of the forecasting performance using several algorithm combinations showed that the various components in these two hybrid frameworks involved the following:

i. Two proposed hybrid predicting structures involve a proper variety of precision supplied in wind speed calculations, which can also apply to wind power sources.
ii. The augmentation of the GA, as well as the PSO components, is not notable, whereas the Wavelet component is important [129].

The approach of wind speed forecasting plays a leading role in providing the safety of wind power performance. In this paper, four different hybrid methods are proposed for high-precision multi-step wind speed forecasting in terms of the Adaboost (Adaptive Boosting) algorithm and the MLP (Multilayer Perceptron) neural networks. In the hybrid Adaboost–MLP forecasting architecture, four important algorithms are adopted for the training and modeling of MLP neural networks, including the GD-ALR-BP algorithm, GDM-ALR-BP algorithm, CG-BP-FR algorithm and BFGS algorithm. This research aims at investigating the promoted prediction percentages of MLP neural networks by Adaboost algorithm optimization under various training algorithms. The hybrid models in the performance comparison include Adaboost– GD-ALR-BP–MLP, Adaboost–GDM-ALR-BP–MLP, Adaboost–CG-BP-FR–MLP, Adaboost–BFGS–MLP, GD-ALR-BP–MLP, GDM-ALR-BP–MLP, CG-BP-FR–MLP and BFGS–MLP. Two experimental results showed the following: (1) the proposed hybrid Adaboost–MLP forecasting architecture is effective for wind speed forecasting; (2) the Adaboost algorithm has promoted the prediction performance of the MLP neural networks considerably; (3) among the proposed Adaboost–MLP forecasting models, the Adaboost–CG-BP-FR–MLP model has the highest performance; and (4) the improved percentages of the MLP neural networks by the Adaboost algorithm decreased step by step with the following sequence of training algorithms: GD-ALR-BP, GDM-ALR-BP, CG-BP-FR and BFGS [130]. Zhang et al. [131] recommends a hybrid computational design in terms of Sequential Quadratic Programming (SQP) and PSOs, to approach the Combined Unit Commitment and Emission (CUCE) intricacy. Developing a model that comprises both thermal dynamos and wind farms, the suggested hybrid computational design manages the scheduling and greenhouse gasses emissions expenses, and it used a set of mathematical models. The final results cited that the proposed hybrid method is better based on the speed and accuracy. The main contribution of this method is the construction of an emissions unit commitment model that is combined with wind energy and connects the SQP and PSO methods to obtain rapid and higher performance optimization [131].

3.4.2. Solar systems

Various optimization methods have been recommended to identify the parameters of solar cells. Nevertheless, most of them obtain sub-optimal solutions due to their precipitate convergence and their difficulty in overcoming local minima in multi-modal problems. Oliva et al. [132] proposed the use of the ABC (Artificial Bee Colony) algorithm to identify the solar cells' parameters accurately. The ABC algorithm is an evolutionary technique that is inspired by the intelligent foraging habits of honey bees. Comparing this technique with other evolutionary algorithms, ABC manifests a better search capacity to face the multi-modal objective functions. To illustrate the proficiency of the intended approach, it is compared to other well-known optimization methods. The experimental results demonstrate the high performance of the proposed method in terms of the robustness and accuracy [132]. The measurement of the PVT properties of natural gas in gas pipelines, gas storage systems, and gas reservoirs requires accurate values of the compressibility factor. Although the equation of state and empirical correlations were utilized to estimate compressibility factor, the demands for novel, more reliable, and easy-to-use models encouraged the researchers to introduce modern tools such as artificial intelligence systems. This paper introduces PSO and GA as population-based stochastic search algorithms to optimize the weights and biases of the networks and to prevent trapping in local minima. Hence, in this paper, GA and PSO were used to minimize the neural network error function [133].

An absolute mathematical paradigm is a useful tool for simulation, estimation, and management as well as the optimization of solar cell operations. This approach is useful because of the nonlinearity of the solar cell models and the limitations of traditional optimization methods in the identification of unknown factors. Simulated Bee Swarm Optimization (ABSO) is a newly proposed algorithm that is encouraged by the intelligent characteristics of honey bees. In this paper, the proposed ABSO-based parameter identification procedure is described in terms of diode models that are composed of a single and double models for a 57-mm diameter commercial (R.T.C.) silicon solar cell. The final results showed that they are quite favorable and outperform those that are conducted by the other research methods [134].

3.4.3. Other Hybrid systems

Recently, it has become obvious from studies that hypotheses based on Knowledge-based professional systems have become important instruments for scientists and engineers. Today, it is not easy to arrive at solutions by previous methods because there are many attractive features that lead to addressing real and difficult engineering problems. Furthermore, by the growing worldwide demand for various types of energy, highly developed intelligent forecasting techniques are necessary to establish the basics of making decisions. Thus, in this study, a new approach was presented to create professional systems to simulate various types of energy requests with related factors and pressures. The capability of this method is evaluated by implementing it in three case studies, namely, annual electricity demands, natural gas demands and oil products required in Iran. The results from this method (COR-ACO-GA) provide more accurate and stable calculations than for neuro fuzzy systems (ANFISs). Additionally, it can support decision makers in appropriate arrangements for a future (subsequent) period [135]. In one investigation, a multi-agent solution (MAS) to energy management in a distributed hybrid renewable energy system was presented. This system has constituents, characteristics, and excitation devices. The validation of the MAS showed its feasibility in achieving all of the system requirements. Therefore, five varieties of agents are offered, which for each agency is built in a three-layered architecture. A macro MAS is also shown in detail. Its framework contains an overall optimization function such as JADE (Java Agent Development). As a result, studies showed MAS to be a suitable solution for the energy management of the distributed hybrid renewable energy system [136]. To enhance the amount of efficiency for future projections in China, this study used a hybrid algorithm and PSO along with GA for a top Energy Demand Estimating (PSO–GA EDE) model. The parameters of the three types of approaches in the model (linear, exponential, and quadratic) was optimized by PSO–GA, while applying determinants, such as GDP, economic structure, population, rate of urbanization, and energy consumption structure, which influence the demand. The simulation outcomes of the suggested model have increased correctness and reliability compared to other single optimization approaches over 20 years. [137].

Another optimization approach used the ANFIS (Adaptive Neuro-Fuzzy Inference System) to illustrate the PV and wind origins. The algorithm developed is related to "HOMER (Hybrid Optimization Model for Electric Renewables)" with HOGA (Hybrid Optimization by Genetic Algorithms) software, and the final results demonstrate a precision of 96% for wind and PV. PSCAD/EMTDC was used to simulate the optimized operation, and the results claimed that a small amount of excess energy is released [108]. In another study, ABSO was used by modeling all of the segments and describing an objective function that was based on the total annual cost. Thus, the maximum acceptable loss in the power supply probability (LPSPmax) is determined for a reliable system. This approach used conditional rules to find the global solution. As a result, $LPSP_{max}$ was set to 0%, 0.3% and 1%, and the PV/WT/FC is a highly cost-effective energy system, and thus, at $LPSP_{max}$ 2%, the WT/FC is the most cost-effective hybrid system [138]. A model using an ANN has been recommended to assess hybrid system behavior. It is associated with wind speed and solar radiation, battery storage life span, and fuel costs. The Hybrid Intelligent Algorithm proposed a combination of analysis of a Monte Carlo simulation method and ANN training in a GA optimization model. It was applied to define input and output data sets that were chosen from 519 tasters, which were later utilized to train the ANNs and decrease the effort that was needed. The generalization power of the ANNs was calculated based on the RMSE (Root Mean Square Error), MBE (Mean Bias Error), MAE (Mean Absolute Error) and R-squared estimators while applying another 200 samples. The conclusions showed that the accessible model can symbolize the main characteristics of a hybrid power in non-reliable operating situations [139].

Berrazouane and Mohammedi [140] presented the development of an optimized fuzzy logic controller (FLC) for operating a standalone hybrid power system, which was based on the cuckoo search algorithm. The FLC inputs are the batteries' state of charge (SOC) and net power flow, and the FLC outputs are the power rates of the batteries, photovoltaic and diesel generator. Data for weekly solar irradiation, ambient temperature and load profile are used to tune the proposed controller by using the cuckoo search algorithm. The optimized FLC is able to minimize the loss of power supply probability (LPSP), excess energy (EE) and levelized energy cost (LEC). Moreover, the results of the CS optimization are better than those of particle swarm optimization PSO for a fuzzy system controller [140]. The tradeoff between the expense and reliability of the method is a major bargain in devising hybrid methods. Thus, the Optimization of a Hybrid Micro-Grid System (HMGS) is examined. A hybrid wind/PV system with battery storage and a diesel generator is used for this purpose, and the Multi-Objective Particle Swarm Optimization (MOPSO) technique is used to find the reliable configuration of the system. Data from a set of wind speeds from three meteorological stations was gathered on an hourly basis in Iran. These selected stations (Nahavand, Rafsanjan, and Khash) were examined for HMGS optimizations. However, the designs of the systems mentioned above and the results agree in that the MOPSO optimization model produces components of appropriate sizes at each location. It is also argued that the use of HMGS can be considered to be a real option for promoting electrification projects and improving energy access within isolated Iranian areas or other developing nations that experience the same or similar climatic situations [141]. Leou [142] used genetic algorithms combined with linear programming (GALP) to find the optimum capacity and working performance of a VRB energy storage system. He considered the operations and maintenance costs, installation expenses and incomes as comprising the energy price for decreasing transmission access expenses and delaying facility investment. Tan et al. [143] used PSO along with a gravitational search algorithm (GSA) to develop a novel optimization model for the siting and sizing of DGs based on real power losses and the grid VA requirement. The final results showed that the proposed approach is effective, robust and proficient for addressing the mixed integer nonlinear optimization problem. Another study proposed a new self-adaptive optimization algorithm based on the θ-Particle Swarm Optimization (θ-PSO) algorithm to find the whole search space globally. In this paper, a novel probabilistic design based on a 2 m Point Estimate Method (2 m PEM) was suggested for considering the uncertainties in the optimum energy management of MicroGrids (MGs) that involve a variety of renewable power sources such as Micro Turbine (MT), Photovoltaics (PVs), storage devices and Wind Turbines (WTs) [144]. Battery storage and Standalone microgrids with renewable sources play a significant role in handling power supply problems in remote areas such as islands. The lifetime parameter of a battery energy storage system must be fully studied to obtain economic and reliable performance of a standalone microgrid as well as to consider

Table 5
Summary of combined different artificial methods.

Reference	Systems studied	Topics covered	Highlights
Wind Systems			
[127]	wind speed and wind power forecasting	• statistical methods	• error is small, which is better than in classical time series methodology; • robust in addressing jumping data; • applicable to both wind speed and wind power forecasting
[128]	trading wind energy in a market environment under uncertainty	• stochastic programming approach	• comparison of optima in the market at different risk levels. • proposed method on a realistic case study
[129]	predict non-stationary wind speeds	• traditional time series examination, • GA • (PSO) and artificial neural networks, • two hybrid forecasting frameworks [(GA)-(PSO)]	• both of them are suitable for different accurateness requirements in wind speed forecasting. • the GA and the PSO components in improving the MLP are not significant, whereas the Wavelet component is significant
[130]	wind speed prediction	• MLP neural networks, including • GD-ALR-BP algorithm • GDM-ALR-BP algorithm • CG-BP-FR algorithm • BFGS algorithm	• Adaboost–the MLP forecasting architecture is effective for wind speed predictions • the Adaboost algorithm has promoted the forecasting performance of the MLP neural networks considerably; • the Adaboost–CG-BP-FR–MLP model has the best performance • Adaboost algorithm decreases step by step with the sequence of training algorithms
[131]	minimize the scheduling cost and greenhouse gases emissions cost	• Sequential Quadratic Programming (SQP) and Particle Swarm Optimization (PSO)	• Implementation of a release unit model with wind energy when combining the SQP and PSO
Solar Systems			
[132]	accurately identify the solar cells' parameters	• ABC (artificial bee colony) algorithm	• high performance of the proposed method in terms of robustness and accuracy
[133]	solar cell systems	• Particle swarm optimization (PSO) • Genetic algorithm (GA)	• Helpful tool for simulation, estimation, management, and optimization of solar cells. • meta heuristic algorithms have attracted significant attention
[134]	diameter commercial (R.T.C. France) silicon solar cell	• Artificial bee swarm optimization (ABSO)	• The results found by the other studied methods
Other Types of Hybrid Systems			
[135]	construct expert systems by ability in modeling and imitation of energy commands	• supportive (COR-ACO-GA)	• to signify that COR ACO GA • adaptive (ANFISs) • (ANNs)
[136]	energy management in a distributed hybrid renewable energy	• multi-agent (MAS) solution	• suitable solution for energy management of a distributed hybrid renewable energy generation system
[137]	optimal Energy Demand Estimating (PSO–GA EDE) model, for China	• Particle Swarm Optimization • and Genetic Algorithm	• proposed model has greater accuracy and reliability than other single optimization methods
[138]	Optimally size a hybrid energy system	• Artificial bee swarm optimization (ABSO)	• stochastic rules to escape local optima and find a global solution
[139]	wind and solar, battery life span, and fuel prices	• ANN (artificial neural network) • Monte Carlo simulation approach • genetic algorithm optimization model	• it can represent the main uniqueness of a typical hybrid power system under doubtful operating conditions
[140]	operating a standalone hybrid power system	• optimized fuzzy logic controller (FLC) • cuckoo search algorithm	• results of CS optimization are better than those of particle swarm optimization (PSO) for a fuzzy system controller
[141]	Hybrid Micro-Grid System (HMGS)	• Multi-Objective Particle Swarm Optimization (MOPSO)	• MOPSO optimization model produces suitable sizing of the elements for each place
[144]	renewable power sources	• 2 m Point Estimate Method (2 mPEM) with a self-adaptive modification PSO method (SAM-θ-PSO)	• A novel self-adaptive modification approach based on the θ-PSO algorithm was proposed. • Several renewable sources such as PV, WT, FC and MT as well as storage devices are considered. • θ-PSO algorithm is used for the first time to solve MG operations management.
[145]	standalone microgrid	• a multi-objective optimization and non-dominated sorting genetic algorithm (NSGA-II)	• Minimize the power generation cost and maximize the life of the lead–acid batteries

the rate of renewable resource utilization. In this research, a standalone microgrid on Dongfushan Island in China was selected as a case study to investigate its economic operation. To achieve this goal, an optimization model composed of operations and maintenance expenses, battery life losses and environmental costs was proposed to find a set of optimum factors of operations strategies. Therefore, a multi-objective optimization and non-dominated sorting genetic algorithm (NSGA-II) was combined to minimize the power generation expenses as well as to maximize the applicable life of the batteries. The final results showed that the suggested approach can optimize the system operation by considering a variety of scenarios, and it can aid users in achieving the optimum operation design of the actual microgrid system [145]. Table 5 indicates a summary of other combined artificial intelligence methods to optimize the hybrid energy systems.

4. Results and discussion

The increase in global energy requirements and the environmental issues that are based on fossil energy performance have encouraged the broad, extensive study of the use of renewable energy techniques instead of traditional fossil fuels. Specifically, hybrid systems, which are described as a combination of renewable and back-up parts or traditional energy sources, play a significant role in finding suitable solutions for handling the challenges that the world confronts today with regard to the sustainability concerns of energy demands and environmental safety.

Hybrid energy systems can be designed and optimized to satisfy the essential requirements of an area based on different factors, such as topography, energy availability of potential resources and types of energy demands. Therefore, the best sizing of the renewable energy sources, which relates to hybrid systems, considerably enhances the economic and industrial aspects of the supplied power performance, such as encouraging the use of such environmentally friendly sources. Several sizing methods are used to find the best hybrid renewable energy system in terms of technology and economy. Finding the optimum design of hybrid renewable energy systems can be important in increasing the economic and technical efficiency of the power supply and in encouraging the extensive use of environmental resources.

Different sizing methodologies in existing software with dissimilar optimization methods are tested here. Thus, every sizing procedure has its attributes, and many new approaches are possible for upcoming usage. Additionally, by the selection of the appropriate method, the types of tools and the users' needs could change. As a result, every developed sizing method has the potential to substantially improve renewable energy systems and, thus, has an enormous significance in the renewable energy area. The ease of leaving out a local minimum and the well-organized capability of finding the universal optimal is the most significant benefit of GAs when using hybrid system sizing. This advantage of code-ability makes it appropriate in sizing studies because this advantage is not accessible in other methods such as PSO, which will be described below. For example, the application of GA and PSO can be encoded into three parameters at most (calculated in the next section), which includes more than three elements, such as in the PV wind fuel cell. Moreover, the GA method does not require non-original data. Nevertheless, the GA is difficult to code because of its complex structure. Furthermore, if the number of parameters is larger, the GA would be more difficult, and there would be an increase in the response time of the GA. The PSO has some benefits over GA, even though both the GA and PSO method have brilliant effectiveness in using the same repeatable searching approach. This method is very easy to implement in any optimization software and is very fast. However, if there are more than three elements, it would be more capable when utilizing the GA approach.

This method is a simple perception that involves an easy implementation in a software environment. Consequently, the calculation time is short, and the requirement for recollection is low. However, the reliability of finding the global optimum in a search area is lower than with a GA-based method. Additionally, the PSO approach is less appropriate than the GA in problems that include a coordinate description of particle bases, which have more than three PSO parameters, and it can only be identified on the x, y, z plane. For example, when considering a PV wind fuel cell hybrid system in which the size is optimized, the x-axis is used to represent the PV panels' numbers. The y-axis is the number of wind turbines, and the z-axis is based on the fuel cell system in the KW. As a result, the three components in using the PSO, which is more capable than the GA, are explained below. However, as mentioned before, if there are more than three available components, then it is more suitable to use the GA method as a replacement for the PSO. In addition, using SA in a hybrid system sizing is not as prevalent as methods such as the GA or PSO, but currently, research interest in SA is increasing, and the approved area of use is growing. The ACS algorithm has been proposed to reduce the distribution of system losses and to balance the factors of radial distribution. Additionally, it has proven to be better than the GA by achieving 44.626% as an average loss reduction. Similar to the GA, the AIS's fundamental optimization has “collection” and “transformation” operatives, which can considerably improve the chance of the algorithm finding the most globally advantageous point.

AIS has a higher potential to be used in sizing studies based on its likeness to the GA and a possible effective route to finding the comprehensive optimum in difficult problems. However, the GA applicability is greater than the AIS in its ability to address a large number of parameters. Most of the time, hybrid optimization methods have been proposed to combine two or more methodologies to improve them, to increase their convergence time in the optimization process. These methods can be characterized because of their flexibility and dynamics during the sizing process. Therefore, they are the most dominant sizing methodologies.

5. Conclusions

This study presents a summary of prior research concerning the use of optimization in artificially intelligent algorithms for designing, planning and controlling problems in the field of hybrid energy systems. There were over one hundred papers reviewed from the major and popular referenced journals in the areas of renewable energy and computational optimization that offer important and useful conclusions for renewable energy research. Optimization studies during the past 2.5 decades by researchers using traditional and new generation methods are analyzed, and optimization methods, including hybrid algorithms, are presented. Artificial intelligence algorithms are mostly used during the past decade because they utilize less computational time and have better accuracy, with good convergence in comparison to traditional methods. In conclusion, this study shows, in the beginning, the number of investigations that use optimization methods in solving renewable energy problems, mainly for wind and solar energy systems. There are many research papers that use heuristic optimization methods, especially GAs and PSOs, to address these problems. However, there are some optimization techniques that involve traditional methods, such as mixed-integer and interval linear-programming, Lagrangian relaxation, quadratic programming, and Nelder–Mead Simplex search. Future research could pave the way for hybridization and multi-objective implementations of bio-inspired solutions. Attempts to exploit the advantages and disadvantages of different algorithms have been made by implementing hybrid algorithms. These approaches have been proven to be faster, more accurate and more powerful than individual systems. The choice of algorithm to be implemented depends solely on the application, and hence, a thorough understanding is needed to justify the merits and demerits. For example, high dimensional problems such as sizing can be addressed better by using PSO rather than GAs. Artificial intelligence techniques are also applied with optimization algorithms in some power system applications. This review will be useful for researchers, to address the complexity and challenges in renewable energy-based hybrid systems research.

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