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*Review Article*

# Bio-Inspired Optimization of Sustainable Energy Systems: A Review

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Sustainable energy development always involves complex optimization problems of design, planning, and control, which are often computationally difficult for conventional optimization methods. Fortunately, the continuous advances in artificial intelligence have resulted in an increasing number of heuristic optimization methods for effectively handling those complicated problems. Particularly, algorithms that are inspired by the principles of natural biological evolution and/or collective behavior of social colonies have shown a promising performance and are becoming more and more popular nowadays. In this paper we summarize the recent advances in bio-inspired optimization methods, including artificial neural networks, evolutionary algorithms, swarm intelligence, and their hybridizations, which are applied to the field of sustainable energy development. Literature reviewed in this paper shows the current state of the art and discusses the potential future research trends.

## 1. Introduction

The demand for energy supply is increasing rapidly in recent years and will probably continue to grow in the future. The realization that fossil fuel resources are becoming scarce and that climate change is related to carbon emissions has stimulated interest in sustainable energy development [1]. In general, sustainable energy development strategies involve three major technological changes: energy savings on the demand side, efficiency improvements in the energy production, and replacement of fossil fuels by various sources of renewable energy [2]. In particular, due to its multifold advantages including inexhaustibility, safety, decrease in external energy dependence, decrease in impact of electricity production and transformation, increase in the level of services for the rural population, and so forth [3], renewable energy is now considered an important resource around the world and regarded as a key component in obtaining a sustainable development of our society.

The implementation of sustainable energy development strategies involves a wide range of design, planning, and control optimization problems. Various conventional optimization methods, such as linear programming [4–6], integer programming [7, 8], mixed integer linear programming [9–12], nonlinear programming [13–16], dynamic programming (DP) [17–20], constrained programming [21, 22], and so forth, have been applied for solving these problems. Nevertheless, current optimization problems in sustainable energy systems become more and more complex, especially when they include the integration of renewable sources in coherent energy systems. This is because most of such problems are nonlinear, nonconvex, with multiple local optima, and included in the category of NP-hard problems [23]. In consequence, those conventional methods might need exponential computation time in the worst case to obtain the optimum, which leads to computation time that is too high for practical purposes [24]. In recent years, modern heuristic optimization techniques, which are stochastic search methods inspired by the concepts and principles of artificial intelligence, have gained popularity in the optimization of sustainable energy systems.

In this paper, we give an overview of the latest research advances in bio-inspired solution methods for sustainable energy development. We particularly focus on the bio-inspired optimization algorithms that have been applied to the design, planning, and control problems in the field of

renewable and sustainable energy systems. We roughly group those methods into three categories, which are artificial neural networks (ANNs), evolutionary algorithms (EAs), and swarm intelligence. Besides, we also describe the recent work about the hybridization of individual methods. These heuristic methods usually do not require deep mathematical knowledge and have been demonstrated to be quite useful and efficient in optimization search for complex optimization problems in science and engineering. We believe that this paper can help researchers to gain knowledge about the major developments emerged throughout the years and find valuable approaches that can be applied in the practice of implementing sustainable energy systems.

The rest of the paper is synthesized as follows: Section 2 reviews the application of ANNs in sustainable energy development, Section 3 summarizes the work about EAs applied to different types of optimization problems in energy, Section 4 presents the recent advances in swarm-based methods used in the field, Section 5 introduces the hybrid techniques combining two or more of above methods, and Section 6 concludes with discussion.

## 2. Artificial Neural Networks

An ANN is a collection of neuron-like processing units with weighted connections between the units, which is inspired by our present understanding of biological nervous systems. Roughly speaking, ANNs use processing elements connected by links of variable weights to form a black box representation of systems [25]. ANNs can be trained by adjusting the weights so as to be able to predict or classify new patterns, and they provide some of the human characteristics of problem solving that are difficult to simulate using other computational technologies. Advantages of ANN include their high tolerance of noisy data, their ability to process patterns on which they have not been trained, as well as that they can be used without much preliminary knowledge about the problem domain. However, ANNs typically involve long training times and have been criticized for their poor interpretability [26].

ANNs are popular for prediction and forecasting nonlinear physical series (such as wind [27] and water lever [28]) which are beyond the capability of linear predictors such as autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA), [29–31]. Since 1990s, various studies have been reported on the applications of ANN in predicting electric loads and energy demands. An early work of Kawashima [32] developed an ANN backpropagation model with three-phase annealing for the first building energy prediction competition held by the American Society of Heating, Refrigerating- and Air-Conditioning Engineers in 1993. Islam et al. [33] proposed an ANN-based weather-load and weather-energy models, where a set of weather and other variables are identified for both models together with their correlations and contribution to the forecasted variables. They applied the models to historical energy, load, and weather data available for the Muscat power system from 1986 to 1990, and the forecast results for 1991-1992 show that monthly electric energy and load can be predicted within a maximum error of 6% and 10%. Al-Shehri [34] used an ANN model for forecasting the residential electrical energy in the Eastern Province of Saudi Arabia, the forecasting result of which is shown to be closer to the real data than that predicted by the polynomial fit model. Azadeh et al. [35] developed a simulated-based ANN and applied it in forecasting monthly electrical energy consumption in Iran from March 1994 to February 2005 (131 months), and the result shows that the ANN model always provides the best solutions and estimation in comparison with other models such as time series.

ANNs have also been applied in midterm and long-term energy forecasting in different industrial sectors, areas, and countries and demonstrated their superiorities in comparison with conventional prediction models [36–41]. In [42] Ermis et al. presented an ANN model which is trained based on world energy consumption data from 1965 to 2004 and applied for forecasting world green energy consumption to the year 2050. It is estimated that world green energy and natural gas consumption will continue increasing after 2050, while world oil and coal consumption are expected to remain relatively stable after 2025 and 2045, respectively.

In recent years, ANN-based models have also been widely used in design and implementation of different kinds of renewable energy systems. For example, in the design of solar energy systems the estimation and calculation of radiation data are very important. Bosch et al. [43] presented an ANN approach for calculating solar radiation levels over complex mountain terrains using data from only one radiometric station. Cao and Lin [44] proposed a diagonal recurrent wavelet neural network which uses historical information of cloud cover to sample data sets for network training and applied their approach in hourly irradiance forecasting in Shanghai, China. Zervas et al. [45] developed an ANN-based prediction model of global solar irradiance distribution on horizontal surfaces, which has been applied to the meteorological database of NTUA, Zografou Campus, Athens.

In the same manner, the prediction of water level is fundamental for ocean energy generation. Huang et al. [46] developed an ANN for water level predictions, which has been applied to coastal inlets taking into account long-term water level observations. Kazeminezhad et al. [47] studied an ANN-based fuzzy inference system for predicting wave parameters, with an application to the data set comprising of fetch-limited wave data and over water wind data gathered from deep-water location in Lake Ontario.

The performance of photovoltaic system heavily depends on the meteorological conditions, and sizing represents an important part of photovoltaic systems design, that is, the optimal selection of the number of solar, cell panels, the size of the storage battery, and the size of wind generator to be used for certain hybrid applications [48]. ANNs have the capability to model complex, nonlinear processes without having to assume the form of the relationship between input and output variables, and thus ANN-based models, including adaptive ANN [49, 50], recurrent ANN [51], radial basis function network (RBFN) [52], have been successfully applied for sizing of photovoltaic systems.

## 3. Evolutionary Algorithms

Evolutionary algorithms (EAs) are stochastic search methods inspired by the principles of natural biological evolution for computationally difficult problems. They are very suitable for complex engineering optimization problems which may be multimodal, nondifferentiable, or discontinuous and thus cannot be solved by conventional gradient-based methods. In general, An EA simultaneously evolves a population of possible solutions and also returns a population of solutions. Typical EAs include genetic algorithms (GAs) [53], evolutionary programming (EP) [54], evolution strategies (ES) [55], differential evolution (DE) [56], and biogeography-based optimization (BBO) [57]. The advantages of EAs include their relative simplicity of implementation, inherent parallel architecture, and scalability to high-dimensional solution spaces.

Moreover, in real-world applications there are a large number of multiobjective optimization problems, that is, problems requiring the simultaneous optimization of several objectives which are often conflicted. For most of such problems, there is no single optimal solution and thus a solution method should search for a set of nondominated (Pareto optimal) solutions, that is, all the solutions such that there exists no other individual better in all the objectives. EAs are capable of finding several members of the Pareto optimal set in a single run of the algorithm, instead of having to perform a series of separate runs as in the case of the traditional mathematical programming techniques [58] and thus are very suitable for tackling with complex multiobjective optimization problems.

*3.1. Genetic Algorithms.* Genetic algorithms (GAs) are of the famous evolutionary algorithms which simulate the Darwinian principle of natural selection and the survival of the fittest in optimization [53]. A GA typically works with a fixed-size population of solutions and uses three genetic operations, namely selection, crossover, and mutation, to modify the solutions chosen from the current generation and select the most appropriate offspring to pass on to the next generations.

A number of researches have been reported on the application of GA in the optimal design and operation of sustainable energy systems. For wind energy systems, Li et al. [59] used a multilevel GA to solve the optimal design problem of integrating the number of actuators, the configuration of the actuators, and the active control algorithms in buildings excited by strong wind force. Li et al. [60] employed a GA to optimize the ranges of gearbox ratios and power ratings of multihybrid permanent-magnet wind generator systems. Grady et al. [61] used a GA to determine the optimal placement of wind turbines for maximum production capacity while limiting the number of turbines installed and the acreage of land occupied by each wind farm. Emami and Noghreh [62] proposed a GA with a new coding and a new objective function with adjustable coefficients for the similar problem, and their algorithm shows better performance on the optimal control of the cost, power, and efficiency of the wind farm. For solar energy systems, Varun and Siddhartha [63] proposed a GA to optimize system parameters in order to maximize the thermal performance of flat plate solar air heaters. Zagrouba et al. [64] adapted a GA to identify the electrical parameters of photovoltaic solar cells and modules to determine the maximum power point from the illuminated current-voltage characteristic. GAs have also been used in geothermal systems [65] and hybrid photovoltaic systems [66–70].

*3.2. Evolutionary Programming and Evolution Strategies.* Evolutionary Programming (EP) was devised in order to evolve finite state machines for the prediction of events on the basis of former observations and has been demonstrated useful for searching the optimum of nonlinear functions [71]. Cau and Kaye [72] proposed a constructive EP approach to minimize the cost of operating a power system with multiple distributed energy storage resources. Their approach combines DP and EP by evolving piecewise linear convex cost-to-go functions and thus decomposes the multistage scheduling problem into smaller one-stage sub-problems which are easy to cope with. Fong et al. [73] developed a simulation-EP coupling method to solve the discrete, nonlinear, and highly constrained optimization problems related to energy management of heating, ventilating, and air-conditioning (HVAC) systems. The application of the method to a local HVAC installation project achieved a saving potential of about 7% as compared to the existing operational settings, without any extra cost. In [74] MacGill presented a dual EP approach integrating with software agents for power system resources to coevolve optimal operational behaviors over repeated power system simulations. The proposed tool was successfully applied to a real-world problem exploring the potential operational synergies between significant PV penetrations and distributed energy storage options including controllable loads.

Evolution strategies (ES) are a class of general optimization methods which evolve a population of solutions by means of variation and selection. Original ES uses a mutation operator that produces a single descendent from a given ancestor, denominated ES-(1 + 1), and was progressively generalized to ES-$(\mu+\lambda)$, that is, several ancestors ($\mu > 1$) and descendents ($\lambda > 1$) in each generation [75]. In [76] Chang used an ES approach to solve optimal chiller loading problem, which takes the chilled water supply temperature as the variable to be determined for the decoupled air-conditioning system. The result shows, the approach outperforms both the Lagrangian method and the GA method. Considering the optimal selection and sizing of distributed energy resources which can be formulated as a nonlinear mixed-integer minimization problem, Logenthiran et al. [77] used ES for the minimization of capital and annual operational cost of DER under a variety of system and unit constraints. Their method was applied to design integrated microgrids for an intelligent energy distribution system project.

*3.3. Differential Evolution.* Differential evolution (DE) approach combines simple arithmetic operators with the classical operators of crossover, mutation, and selection to evolve a randomly generated starting population to a final solution. It is similar to a $(\mu + \lambda)$ ES, but in DE

the mutation is not done via some separately defined probability density function [78]. Chakraborty et al. [79] presented a fuzzy DE method for solving thermal unit commitment problem integrated with solar energy system, where the solar radiation, forecasted load demand and associated constraints are formulated as fuzzy sets considering the error. Slimani and Bouktir [80] developed a DE method to solve the optimal power flow problem, whose objective function is the minimization of the cost of the thermal and the wind generators with different sizes. The method decomposes the optimization constraints of the power system into active constraints manipulated directly by DE, and passive constraints maintained in their soft limits using a conventional constraint load flow.

dos Santos Coelho et al. [81] developed a cultural DE algorithm for optimizing the economic dispatch of electrical energy using thermal generators and validated their approach on a test system consisting of 13 thermal generators whose nonsmooth fuel cost function takes into account the valve-point loading effects. Suzuki et al. [82] studied a large-scale mixed-integer nonlinear problem for generating optimal operational planning for energy plants and developed an $\varepsilon$ constrained DE algorithm to effectively solve the problem without much parameters tuning effort. Hejazi et al. [83] developed a DE algorithm for optimal allocation of energy and spinning reserve, taking all security and power systems constraints in steady state and system credible contingencies into consideration. Lee et al. [84] conducted a comparative study of DE, GA, PSO, and LP methods for solving the optimal chiller loading problem for reducing energy consumption, and the result shows that the DE algorithm achieves the best result. Peng et al. [85] considered a problem in the design of the Earth-Moon low-energy transfer to find the patch point of the unstable manifold of the Lyapunov orbit around Sun-Earth L2 and the stable manifold of the Lyapunov orbit around Earth-Moon L2. They designed an improved differential evolution algorithm which incorporates the uniform design technology and the self-adaptive parameter control method into standard differential evolution to accelerate its convergence speed and improve the stability, and thus effectively solve the problem.

*3.4. Multiobjective Evolutionary Algorithms.* Multiobjective evolutionary algorithms (MOEAs) have received much interest in recent years. A number of metaheuristic algorithms, such as the nondominated sorting genetic algorithm NSGA [86] and the NSGA-II [87], the strength Pareto evolutionary algorithm (SPEA) [88] and the SPEA2 [89], the Pareto archived evolution strategy (PAES) [90], the Pareto differential evolution algorithm (PDE) [91], the nondominated sorting differential evolution (NSDE) [92], and so forth have gained great success in solving multiobjective optimization problems [93].

Benini and Toffolo [94] presented an MOEA for the design of stall-regulated horizontal-axis wind turbines, the aim of which is to achieve the best trade-off performance between the total energy production per square meter of wind park and cost. Their method can optimize the geometrical parameters of the rotor configuration of wind turbines, achieving the best trade-off performance between the two objectives. Zhao et al. [95] employed a GA whose input parameters are the main components of a wind farm and key technical specifications and whose output is an optimal electrical system design of the wind farm which is optimized in terms of both production cost and system reliability. Kusiak et al. [96] proposed an MOEA for evaluating wind turbine performance, where the objectives include the maximization of the wind power output and the minimization of the vibration of the drive train and of the tower. In [97] Kusiak and Song used the MOEA for optimizing wind turbine placement based on wind distribution, including the selection the best turbine combination from a given list of available turbines.

Bernal-Agustín et al. [98] applied the SPEA to the design of a photovoltaic-wind-diesel system, where the objectives include the minimization of both the total cost throughout the useful life of the installation and the pollutant emissions. They later applied the algorithm to an extension of the problem, which adds an objective of the unmet load in the system [99]. Ould Bilal [100] proposed a multiobjective GA for minimizing the annualized cost system and the loss of power supply probability of a hybrid solar-wind-battery system. Montoya et al. [101] combined PAES with simulated annealing (SA) and tabu search (TS) to minimize voltage deviations and power losses in power networks. Thiaux et al. [102] applied NSGA-II to optimize stand-alone photovoltaic systems by reducing the gross energy requirement and minimizing the storage capacity. In [103] Rao and Peng considered a multiobjective optimal model of dispatch of energy-saving and emission reduction generation in the power system and developed a multiobjective DE algorithm with niche strategy for improving the crowing mechanism in the process of Pareto nondominated sorting operation. The experiment shows that their method can achieve better result than NSGA-II and NSDE.

## 4. Swarm Intelligence

The expression "swarm intelligence" was originally used in the context of cellular robotic systems to describe the self-organization of simple mechanical agents through nearest-neighbor interaction [104]. Bonabeau et al. [105] extended the definition to include "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies." Since the 1990s, a number of swarm-based algorithms, including particle swarm optimization (PSO) [106], ant colony optimization (ACO) [107], artificial bee algorithms [108, 109], artificial immune systems (AIS) [110] have been proposed for difficult optimization problems especially with large continuous or combinatorial search spaces.

*4.1. Particle Swarm Optimization.* PSO is another population-based global optimization technique that enables a number of individual solutions, called particles, to move through a hyperdimensional search space to search for the optimum. Each particle has a position vector and a velocity vector, which are adjusted at iterations by learning from a local best found by the particle itself and a current global

best found by the whole swarm. Empirical studies have shown that PSO has a high efficiency in convergence to desirable optima and performs better than GA and other EAs on many problems [111].

AlRashidi and EL-Naggar [112] employed a PSO algorithm for estimating annual peak load forecasting in an electrical power system, the aim of which is to minimize the error associated with the estimated model parameters. Their approach was validated on actual recorded data from Kuwaiti and Egyptian networks. Niknam and Firouzi [113] developed a PSO algorithm combined with simplex search, for estimating load and renewable energy source output on the power systems, and their comparative experiment show that the PSO performs better than several EAs and other swarm-based algorithms.

Amjady and Soleymanpour [114] developed a modified adaptive PSO for daily hydrothermal generation scheduling, which is a complicated nonlinear, nonconvex, and nonsmooth optimization problem with discontinuous solution space. As some other adaptive PSOs [115, 116], their method dynamically changes the inertia weight and acceleration coefficients of the algorithm to increase activities of particles to explore broad space. Lee [117] applied PSO to solve short-term hydroelectric generation scheduling of a power system with wind turbine generators. Kongnam and Nuchprayoon [118] used PSO for the control problem of a wind turbine, which involves the determination of rotor speed and tip-speed ratio to maximize power and energy capture from the wind. Khanmohammadi et al. [119] developed a method based on PSO and Nelder-Mead algorithms for determining the optimal unit commitment (startups and shutdowns scheduling) of hydropower plants. López et al. [120] presented a binary PSO-based method to accomplish optimal location of biomass-fuelled systems for distributed power generation with forest residues as biomass source, and the results outperformed those obtained by a GA when maximizing a profitability index taking into account technical constraints. In [121] the authors also applied a PSO algorithm for the optimal location and supply area for biomass-based power plants. There are also a number of researches reported on the application of PSO in the design and control of hybrid photovoltaic systems [122–126].

Economic dispatch problems, the main aim of which is to schedule the committed generating units output so as to meet the required load demand at minimum cost satisfying all unit and system operational constraints, typically have nonlinear, nonconvex type objective function with intense equality and inequality constraints. Mahor et al. [127] presented a yearly (2003–2008) review of work of application of PSO to solve the various economic dispatch problems. The algorithms include linearly varying inertia weight PSO [128, 129], PSO with constriction factor and inertia weight [130, 131], PSO with linearly varying inertia weight with constriction factor [132], chaotic PSO [133–135], and multiobjective PSO [136–139]. It was suggested that PSO algorithms (in particular those with time varying control parameters) can give an improved results within less computational time in comparison to conventional methods, but still further improvements in PSO algorithms are required, especially for real-time scheduling problems.

*4.2. Ant Colony Optimization.* Ant colony optimization (ACO) algorithms mimic the behavior of real ants living in colonies that communicate with each other using pheromones in order to accomplish complex tasks such as establishing a shortest path from the nest to food sources [107]. Li et al. [140] applied an ACO algorithm to the optimal design of solar energy dynamic power system in space station, with the aim to minimize the launching mass of the system subject to a set of constraints on parameters including pressure, temperature, compression coefficient, numbers and diameter of heat exchangers, height of recycling refrigerant, and so forth. Considering the optimal sizing of the design of standalone hybrid wind/photovoltaic power systems, Xu et al. [141] used ACO to minimize the total capital cost, subject to the constraint of the loss of power supply probability calculated by simulation. Foong et al. [142] considered a power plant maintenance scheduling optimization formulation incorporating the options of shortening the maintenance duration and/or deferring maintenance tasks in the search for practical maintenance schedules and developed an improve ACO algorithm for solving the problem. Warner and Vogel [143] considered planning of an energy supply network by simultaneously choosing the plants and the optimal network and implemented an ACO algorithm for the problem. See et al. [144] used ACO for determining optimal parameter values to the control model of energy extraction and thus improving the performance of wave energy converters as well as their long-term economic value.

Toksari [145] proposed an ACO electricity energy estimation model for forecasting electricity energy generation and demand, taking population, gross domestic product (GDP), import and export into consideration. He found that the model with quadratic equations can provide better fit solution due to the fluctuations of the economic indicators. The proposed model was applied to indicate Turkey's net electricity energy generation and demand until 2025. Baskan et al. [146] used ACO for estimating the transport energy demand of Turkey using gross domestic product, population, and vehicle-km. It is also expected that the work will be helpful in developing highly applicable and productive planning for transport energy policies.

*4.3. Artificial Bee Algorithms.* Artificial bee algorithms simulate the intelligent foraging behavior of a honeybee swarm. Two most popular algorithms are the artificial bee colony (ABC) algorithm and the honey bee mating optimization (HBMO) algorithm [147]. Niknam et al. [148] presented a multiobjective HBMO algorithm for the siting and sizing of renewable electricity generators, in order to optimize the placement of renewable electricity generators by considering objective functions including losses, costs of electrical generation, and voltage deviation. In [149] Niknam et al. also proposed an improve a HBMO algorithm for economic dispatch in power systems, with the aim to get maximum usable power using minimum resources. Abu-Mouti and El-Hawary [150] considered a dynamic economic dispatch problem, whose

aim is to determine the optimal power outputs of online generating units in order to meet the load demand subject to satisfying various operational constraints over finite dispatch periods, and they applied an ABC algorithm to solve the problem.

Vera et al. [151] proposed a binary honey bee foraging (HBF) swarm approach for searching the optimal location, biomass supply area, and power plant size that offer the best profitability for investor. Experimental results show that the HBF approach method outperforms PSO and GA. Hong [152] presented an electric load forecasting model based on a chaotic ABC algorithm combined with the seasonal recurrent support vector regression model, and the experiments indicated that the model can provide a promising forecasting performance for electric load.

*4.4. Artificial Immune System (AIS).* Inspired by the theoretical immunology, observed immune functions, principles, and models, AIS stimulates the adaptive immune system of a living creature to unravel the various complexities in real-world engineering optimization problems. Abdul Rahman et al. [153] developed an AIS algorithm for the economic dispatch problem, which uses the total generation cost as the objective function. Through genetic evolution, the antibodies with high affinity measure are produced and become the solution, and the algorithm converges within an acceptable execution time and highly optimal solution for economic dispatch with minimum generation cost. Coelho and Mariani [154] coped with the problem by using a chaotic artificial immune network approach, which has been demonstrated by the experiments to be an effective alternative to schedule the committed generating unit outputs to meet the required load demand at minimum operating cost while satisfying system constraints. Recently, Arsalani and Seddighizadeh [155] used an AIS algorithm to minimize the deviation of bus voltage from its nominal value as well as the loss of energy in a power system. The main advantage of the algorithm is that it prevents many times repetition of similar solutions, and the result shows that the algorithm can achieve a solution that meets a level of preferences better than that required although the threshold is determined by means of fuzzy logic to reflect the imprecise nature of optimization objectives.

## 5. Hybrid Methods

By exploiting the advantages and disadvantages of two or more solution methods, we have a chance to obtain a powerful approach that is much more competitive than any individual method. Research and development on hybrid bio-inspired methods in sustainable energy systems have grown dramatically since the late 1990s.

Mellit and Kalogirou [156] studied the combination of GA and ANN for optimal sizing of stand-alone photovoltaic systems. Firstly the GA was used to optimize the sizing parameters of sites, and then the ANN was used to predict the optimal parameters in remote areas. Mellit later developed a hybrid model combining adaptive-network-based fuzzy inference system (ANFIS) and GA and demonstrated that the model with ANFIS presents more accurate results [157]. Chang and Ko [158] designed a hybrid heuristic method which combines PSO with nonlinear time-varying evolution and ANN in order to determine the tilt angle of photovoltaic modules with the aim of maximizing the electrical energy output of the modules.

Li et al. [159] proposed a method combining AIS and PSO, for optimal load distribution among cascade hydropower stations. Their hybrid method involves the immune information processing mechanism into PSO and thus improves the ability to find the globally excellent result and the convergence speed with its special concentration selection mechanism and immune vaccination. Yang et al. [160] combined GA and ABC into a bee evolutionary genetic algorithm (BEGA), which has characteristics of higher precision and faster convergence rate and has been effectively applied to a problem of minimizing the energy consumption of central air-conditioning system without lowering the degree of comfort. The test on a common load distribution case shows that the hybrid method can achieve an energy-saving rate at 25.1%.

Kıran et al. [161] proposed a hybrid method of PSO and ACO for estimating energy demand, PSO for solving continuous optimization part and ACO for discrete part. The experiments demonstrated that the hybrid method outperforms both the individual PSO and ACO. In [162] Ghanbari et al. combined GA and ACO to model and simulate fluctuations of energy demand under the influence of related factors. Firstly the GA is used for generating data base of the expert system, and then the ACO is used for learning linguistic fuzzy rules such that degree of cooperation between data base and rule base increases. Results showed that the method can provide more accurate-stable results than ANFIS- and ANN-based approaches.

## 6. Discussion and Conclusion

We have summarized the recent research advances in bio-inspired solutions applied to the design, control, and implementation of sustainable energy systems. Typical illustrations are addressed for ANNs, EAs, swarm-based algorithms, and their hybridizations. Representative works are summarized to help readers have a general overview of the state-of-the-art and easily refer suitable methods in practical solutions.

The first finding of this paper is that the number of research papers on bioinspired optimization algorithms on sustainable energy problems has increased dramatically since 1990s. A large percent of early work was GA related. However, in recent years, DE has become more popular in the category of EAs, and swarm-based methods have gained more and more attentions of the researchers and practitioners. In the last three years, we found that PSO algorithms have become one of the most widely used methods in the field of renewable and sustainable energy development.

In general, none of the individual methods could perform better than all the other methods on all kinds of problems, suggesting that customized methods need to be carefully chosen or designed according to the respective problem. But researchers and practitioners can learn from the experiences

of early researchers. For example, on most problems of unit sizing of stand-alone hybrid energy systems, PSO typically outperforms GAs [163], mainly because PSO algorithms are more suitable for high-dimensional optimization problems, and improved versions of PSO are less sensitive to multiple local optima than GAs.

With the increasing importance and complexity of energy systems, we are facing the challenges to promote the performance, reliability, and scalability of solution methods [164, 165]. In consequence, it can be anticipated that future research will continuously put great emphasis on the hybridization of bio-inspired methods. In addition, more and more real-world problems in sustainable energy consider more than one objective. It can be expected that multiobjective bio-inspired optimization algorithms and parallel processing will be promising research areas in this field [166]. Moreover, current studies on multiobjective algorithms combing more than one metaheuristics are still rare, and we think that this can be a valuable direction for the researchers.

Today's new computational paradigms, such as quantum computing [167], DNA computing [168], and fractal computing [169–172], provide valuable inspiration for creating new heuristics for extremely difficult problems. Thus, the extensions of current bio-inspired methods based on these new paradigms are expected to achieve dramatic improvement on computational performance. For example, quantum-inspired EAs are regarded as one of the three main research areas related to the complex interaction between quantum computing and EAs [173]. In the aspect of quantum computing, if applying ANNs, it is worth considering time series models in that aspect as that discussed by Bakhoum and Toma [174, 175]. We believe that the fruits of these researches are continuously becoming new technological solutions to new open problems, and the full potential is far from being reached.

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