IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 1, 2019, accepted March 26, 2019, date of publication March 29, 2019, date of current version April 24, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2908227

An Improved Brain Storm Optimization for a Hybrid Renewable Energy System

XING-RUI CHEN[1], JUN-QING LI[1,2,3], YUYAN HAN[2], BEN NIU[1], LILI LIU[2], AND BIAO ZHANG[2]

[1]School of Information Science and Engineering, Shandong Normal University, Jinan 250014, China
[2]School of Computer, Liaocheng University, Liaocheng 252059, China
[3]Key Laboratory of Computer Network and Information Integration, Southeast University, Nanjing 211189, China

Corresponding author: Jun-qing Li (lijunqing@lcu-cs.com)

This work was supported in part by the National Science Foundation of China under Grant 61773192 and 61803192, in part by the Shandong Province Higher Educational Science and Technology Program under Grant J17KZ005, in part by the Key Laboratory of Computer Network and Information Integration, Southeast University, Ministry of Education, under Grant K93-9-2017-02, in part by the State Key Laboratory of Synthetical Automation for Process Industries under Grant PAL-N201602, in part by the Special fund plan for local science and technology development lead by central authority, and in part by the major basic research projects in Shandong under Grant ZR2018ZB0419.

ABSTRACT In this paper, an improved brain storm optimization (BSO) algorithm is proposed to solve the optimization problem in a hybrid renewable energy system. The objective of the proposed algorithm is the minimization of the annualized costs of the system (ACS), the loss of power supply probability (LPSP), and the total fuel emissions. In the proposed algorithm, first, the K-Means clustering method is embedded to make the same clusters have similar solutions. Then, the distance of a city block is taken as the distance measure, which makes the solution feasible. Then, to measure the merits and demerits of each individual, the composite index is utilized as the fitness value. In addition, to improve the efficiency of the algorithm, a pair of crossover and mutation strategies are designed in detail. Finally, a set of realistic instances are used to test the performance of the proposed algorithm, and after detailed experimental comparisons, the competitive performance of the proposed algorithm is verified.

INDEX TERMS Brain storm optimization, city block distance, K-Means method, hybrid renewable energy system.

I. INTRODUCTION

During recent years, energy issues have become an increasingly important factor for economic and social development. As a result, researchers are looking for renewable clean energy, such as wind, solar, biomass, and tidal energy [1], to replace traditional fossil fuels. However, some renewable energies are susceptible to local weather and climate characteristics and are disadvantageous and unstable [2]. A hybrid renewable energy system (HRES) can effectively improve the reliability of the power supply system, reduce the power generation costs, and overcome the instability of a single energy form by combining different forms of renewable energy [3]–[6], therefore improving the overall efficiency of the system [5], [6]. Fig. 1 presents a block diagram of a hybrid wind/photovoltaic (PV)/diesel system. It can be seen from Fig. 1 that the various components of the HRES system should be optimized, and the performance of the hybrid system will be directly affected by the optimization results [7].

The linear programming method was first used in the optimization design of the HRES [8]–[10]. To consider the optimization problem with a single objective, Kuznia et al. proposed a random mixed integer programming model for the design of a hybrid power generation system, which includes a fan, an energy storage device, a transmission network, and components such as thermal generators [11]. Akella et al. constructed a linear programming model to optimize the design of a hybrid energy system consisting of small hydroelectric generators, photovoltaic panels, fans and biomass [12]. To consider two or more objectives, such as the system reliability and emissions indicators, Kaabeche et al. proposed an iterative optimization technique to optimize the reliability and costs of a landscape hybrid system [13]. Ashok et al. used the quasi-Newton method to find the best

The associate editor coordinating the review of this manuscript and approving it for publication was Arup Kumar Goswami.

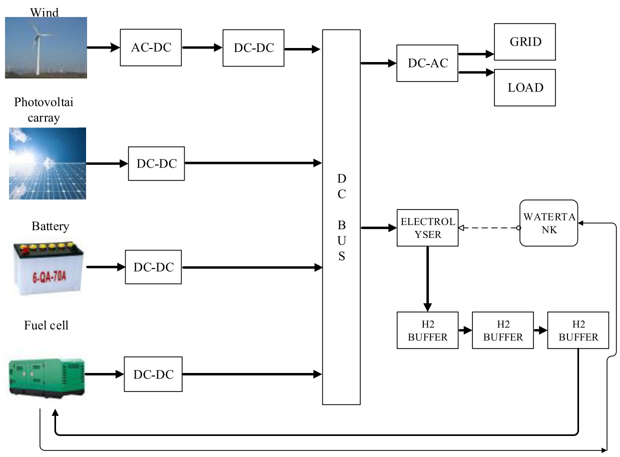


FIGURE 1. Block diagram of a hybrid wind/PV/diesel system.

combination of components in a wind-light-water-storage system, which maximizes the system reliability and minimizes the costs [14]–[17].

With the rapid development of multi-objective evolutionary algorithms, many researchers have proposed a series of methods for multi-objective problems. Katsigiannis et al. proposed a two-objective optimization model and used the non-dominated sorting genetic algorithm (NSGA-II) to optimize the Pareto frontier for the optimal allocation of hybrid energy systems with the goal of minimizing the total system costs and greenhouse gas emissions during the life cycle [18]. Bilil et al. used a penalty factor to constrain the resulting imbalance between renewable energy and demand and ensure system reliability, where the two objectives of the system costs and reliability were minimized [19]. Hakimi and Tafreshi used particle swarm optimization (PSO) to determine the number of system components and minimize the total costs while ensuring that the energy requirements are met [20]. Borhanazad et al. used a multi-objective PSO method and a weighting method to optimize a hybrid system with wind and light energy with the goal of minimizing the unit energy costs and the missing power supply rate [21]. Kamjoo et al. considered the uncertainty of renewable energy [22]. Wang et al. proposed a multi-objective combinatorial optimization model [23]. Abedi et al. established a multi-objective optimization model that minimized the total costs, failures of meeting load requirements and pollutant emissions [24]. Bilal et al. developed a multi-objective genetic algorithm [25]. Shi et al. minimized the annual costs of the system, the fuel emissions and the loss rate of the power supply [26]. Other types of meta-heuristics for solving the HRES can be found in [11], [27].

During recent years, many types of meta-heuristics have been developed to solve realistic optimization problems, such as the artificial bee colony (ABC), teaching-learning-based optimization (TLBO), invasive weed optimization (IWO), particle swarm optimization (PSO), Fruit Fly Optimization Algorithm (FOA), and brain storming algorithm (BSO). Many researchers have applied the ABC algorithm to solve the distributed flow shop problem [28], [29], crowd evacuations in buildings [30], steelmaking scheduling problems [31], the flexible job-shop scheduling problem [32]–[34], the large-scale hybrid flow shop scheduling problem with limited buffers [35], cooperative co-evolution based on hierarchical communication model [36], the hybrid flexible flowshop problem [37], and the distributed flow shop problem [38]–[43]. Other types of scheduling problems, including flexible job shop scheduling and vehicle routing problems, have also been solved by the classical optimization algorithms, such as genetic algorithm, shuffled frog-leaping algorithm, and the tabu search algorithm [44]–[49]. The TLBO has also been recently developed and applied to solve many types of problems, such as chiller loading optimization problems [50] and realistic flowshop rescheduling problems [51]. The IWO has been applied to solve chiller loading optimization problems [52], [53] and lot-streaming flowshop scheduling problems [54], [55]. The PSO has been applied to solve permutation flow shop scheduling problem [56]. The FOA has successfully used to solve the Realistic Hybrid Flowshop Rescheduling Problem [57], [58] and continuous function optimization problems [59]. Other optimization algorithms [60], such as the harmony search (HS) algorithm [61], and the artificial fish swarm algorithm (AFS) [62], have also been researched. In addition, multi-objective optimization algorithms have also been developed. The typical applications of the multi-objective optimization algorithms including the MOEA/D method [63], the dynamic decomposition method [64], the cognitive-radio-based Internet of Things [65], the hybrid flow shop problems [66], the financial loss problems [67], the rescheduling congestion management problems [68], the multi-attribute group decision problems [69], the stochastic nonlinear systems [70], the flexible job shop problems [71], the lot-streaming flow shop problems [72], the blocking flow shop problems [73]–[74], and other applications [75–84]. The BSO algorithm was proposed in 2011, and it simulates a kind of collective brainstorming behavior. The BSO algorithm has been used to solve many practical application including continuous optimization problems and other types of scheduling problems [85]–[87]. The BSO has been verified to be an efficient algorithms, especially for the realistic application.

In this paper, to solve the optimization problems in a hybrid and renewable energy system, we develop an improved BSO algorithm. The remainder of this paper is organized as follows. Section II briefly describes the components of the model of the mixed renewable energy system. Then, Section III illustrates the problem description and optimization objectives. Section IV presents the related algorithm and the proposed algorithm is detailed in Section V. Experimental comparisons and analyses are given in Section VI. Finally, Section VII concludes by presenting the contributions and plans for future works.

II. MODELING THE HRES

This section describes the various components of a hybrid renewable energy system.

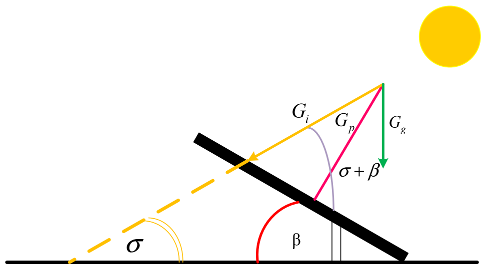


FIGURE 2. Solar photovoltaic panels irradiate sunlight.

A. MODELING THE PHOTOVOLTAIC SYSTEM

The mathematical model of photovoltaic power generation often only considers the light intensity and the ambient temperature as variables [17]. The inclination of the photovoltaic panel to the position of the sun's illumination affects the output power of the photovoltaic panel, and therefore, the tilt angle of the photovoltaic panel is an important decision variable in the system. The photovoltaic panels and solar radiation components are shown in Fig. 2.

$$\delta = \theta \times \sin(360^\circ \times \frac{284+n}{365}) \tag{1}$$

$$\sinh = \sin\varphi \sin\delta + \cos\varphi \cos\delta \cos\tau \tag{2}$$

$$\tau = \frac{360}{24}(12-lt) \tag{3}$$

The incident radiated solar energy on an inclined photovoltaic plate is calculated by equation 1. First of all, it is necessary to calculate the solar declination angle δ and the solar height angle h. The declination angle is the angle between the equatorial plane of the earth and the center line of the earth and the sun; the solar height angle is the angle between the incident direction of the sun and the horizontal ground. Where θ is the inclination of the earth's axis to the earth's orbital plane, n is the number of days in one year when January 1st is recorded as one, φ is the geographical latitude, τ is the angle of the earth's rotation every hour, and lt is the local time.

$$G_{\mathrm{i}} = \frac{G_g}{\sinh} \tag{4}$$

$$G_p = G_i \sin(\sigma+\beta) \tag{5}$$

Then the incident radiation G_i on the inclined photovoltaic plate is calculated, and G_g is the horizontal component of solar radiation. The operational component G_p of solar radiation perpendicular to the inclined surface is calculated. The maximum output power of the photovoltaic plate at time t, taking into account the surrounding temperature effect, which can be reflected in the following formula.

$$T_C(t) = T_A(t) + \frac{NOCT-20}{800} G_p(t,\beta) \tag{6}$$

$$I_{SC}(t) = [I_S + K_I(T_C(t)-25)]\frac{G_P(t,\beta)}{1000} \tag{7}$$

$$V_{OC}(t) = V_O - K_V \cdot T_C(t) \tag{8}$$

$$P_M(t,\beta) = N_S \cdot N_P \cdot V_{OC}(t) \cdot I_{SC}(t,\beta) \cdot FF(t) \tag{9}$$

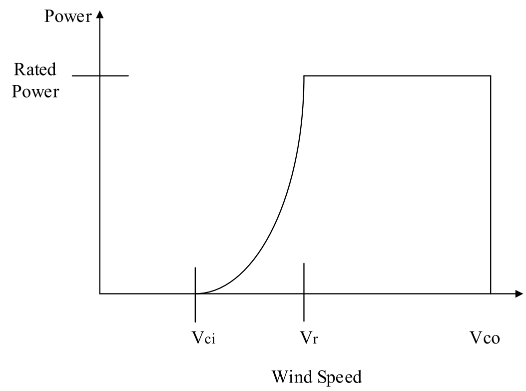


FIGURE 3. Wind turbine output power.

$T_C(t)$ is the temperature of the photovoltaic panel at time t, and $T_A(t)$ is the temperature of the surrounding environment of the t-time system. NCOT (Nominal Cell Operating Temperature) indicates the rated operating temperature of the battery with the data supplied by the manufacturer. I_S and V_O are the short-circuit current and open-circuit voltage of photovoltaic cells under standard test conditions. K_I and K_V are the corresponding temperature coefficients, respectively. $P_M(t,\beta)$ is the resulting power of a photovoltaic array consisting of N_S series and N_P parallel photovoltaic panels. $FF(t)$ is a filling factor, which is linked to the properties of photovoltaic cells.

B. MODELING THE WIND TURBINE

The rated output power of the wind power is set to match the specific rated wind speed. Since the energy is proportional to the cube of the wind speed, the power of the wind turbine varies with the wind speed. The description of the fan is shown as below.

When the actual wind speed is lower than the cut-in wind speed of the fan, and the output power of the fan is less than the loss of the system, then the fan is in a shutdown state. The output power of the fan increases to the third power of the wind speed until the rated wind speed is reached, when the wind speed is higher than the cut-in wind speed. When the wind speeds is higher than the rated wind speed and lower than the cut-out wind speed, it is necessary to take appropriate measures to limit the output power of the fan. The fan must stop to ensure the safety of the system, when the wind speed exceeds the cut-out wind speed.

The model formula for wind power generation is as follows:

$$P = \begin{cases} 0, & \mathrm{v}<\mathrm{V_{ci}} \\ 1/2C_pMAv^3, & V_{ci} < v < V_{\mathrm{r}} \\ P_R, & V_r < v < V_{co} \\ 0, & v > V_{co} \end{cases} \tag{10}$$

The wind speed v at each time is the input to the model. Cp is the performance coefficient of the fan, which is the output power of a fan divided by the maximum wind power. M is the air density, A is the area swept by the rotor, and

P_R is the rated power of the fan. V_{ci} is the cut-in speed of the fan which is set as 4 m/s, the rated wind speed V_r is set to be 14 m/s, and the cut-out wind speed V_{co} is set as 20m/s.

The wind speed varies with the height of the tower, which results in a different model.

The following model is utilized:

$$v = v_h(\frac{H_{wg}}{H_r})^x \tag{11}$$

where v is the wind speed, H_{wg} is the fan height, v_h is the wind speed measured by the reference height H_r, and x is the exponential law coefficient.

C. MODELING THE BATTERY

A battery pack is used to store excess energy. When the power generation cannot satisfy the load requirements, the battery pack can be used to fulfill the load requirements. Most battery models take into account the state of charge (SOC), which should remain within the maximum and minimum values that are given by the manufacturer to ensure battery pack safety.

The SOC of the battery pack is based on the relationship between the renewable energy generation and the load power demand. The SOC of the battery pack at each simulation time step can be calculated by the following:

$$SOC(t+1) = SOC(t) + \frac{(P_{bat}(t)/V_{bus}) \cdot \Delta t \cdot \eta_{bat}}{C_n} \tag{12}$$

where $P_{bat}(t)$ is the input/output power of the battery; V_{bus} is the DC (Direct Current) bus voltage; Δt is the simulation time step, whose value is 1 hour; η_{bat} is the bidirectional charge-discharge efficiency, considered 80% in the process of charging and 100% for the duration of discharging; and C_n is the total rated capacity of the energy storage battery pack.

D. MODELING THE DIESEL ENGINE

The introduction of diesel generators can further increase the reliability of hybrid renewable energy systems, but it will also raise the costs of the system. Meanwhile, the consumption of fossil fuels such as diesel will add harmful pollutants and greenhouse gas emissions.

The fuel consumption of a diesel generator depends on its own nature. To simplify the calculation, the fuel consumption of the diesel generator F_C can be approximated as a linear function of its power output. The expression is as follows:

$$F_c = A_{dg}P_r + B_{dg}P_{dg} \tag{13}$$

where P_r is the rated power of a diesel generator; P_{dg} is the output power of a diesel generator; A_{dg} and B_{dg} are the coefficients of the fuel consumption curve, which are set to 0.08231/ kWh and 0.256 l/kWh, respectively.

In addition to the commonly used components, such as photovoltaic power generation, fan power generation, energy storage systems, and diesel generators, the hybrid renewable energy systems also contain accessories such as a rectifier, inverter, and control switch and so on. These attachments are typically low-cost, simple in nature, and have little impact on the construction of the overall model of the system. Therefore, it is simplified in system modeling [23].

III. PROBLEM DESCRIPTION

Based on Zaragoza, Spain, this paper studies a hybrid renewable energy system consisting of solar energy, wind energy, diesel generators and battery packs that can satisfy the load demand in the area.

For the planning and design of hybrid renewable energy systems, different optimization objectives will produce distinct optimization results, thus resulting in different optimal system configurations. It can be seen from the research status of the HRES that there are many goals that can be considered in the optimal design of hybrid renewable energy systems, but there is only a single objective rather than multiple targets. Although these optimization goals are not exactly the same in terms of their meanings, they can be divided into three categories: economic goals, reliability goals, and environmental benefit goals.

A. HRES OPTIMIZATION GOAL

In the optimal design of the system, the annualized costs of the system (ACS), the loss of power supply probability (LPSP) and the fuel emissions are selected as the optimization objectives from the three above categories of optimization goals.

The annualized cost of system (ACS) is the annual costs that are calculated based on factors such as the system's age, the annual interest rate and the inflation rate, which can reasonably reflect the economic benefits of the system for one year [17].

$$ACS = IC \times CRF + C_r \times SFF + OMC \tag{14}$$

where IC represents the annualized initial investment cost; CRF represents the capital recovery factor, which is a proportion of the amount of money that can be recovered each year at a specified interest rate; C_r is the replacement cost of the component;SSF represents the sinking fund factor, which converts the replacement cost to the average annualized replacement cost over the life of the component; and OMC represents the operating and maintenance costs for the year.

Due to the intermittent and random nature of renewable energy, reliability analysis is an important goal to be considered in the HRES optimization process. The reliability of the system refers to the system's response requirements.

The loss of power supply probability (LPSP) is defined as the ratio of the total time that the system's capacity cannot meet the load demand. LPSP ranges from [0],[1], where 0 means that the load can always be satisfied, and 1 means that the load will always not be satisfied throughout the cycle. The formula for calculating the LPSP is as follows:

$$LPSP = \frac{LOLE}{T} \tag{15}$$

where the loss of load expected ($LOLE$) refers to the expected value of the load exceeding the amount of electricity available over a period of time, and T is the sum time of one year, i.e., 8760 hours.

With respect to environmental performance objectives, many studies have considered fuel emissions, including greenhouse gas emissions. CO_2 is usually representative and is the main gas that is responsible for the Greenhouse Effect. In an HRES, the fuel emissions mainly come from the diesel generator, and most of its emissions are CO_2. Therefore, many literatures directly use the CO_2 emissions of the diesel generator to represent the gas emissions of the system, and regard it as the optimization goal for the environmental benefit. Emissions can be calculated using formula (16):

$$F_e = \sum_{t=1}^{T} F_c(t) \times E_f \tag{16}$$

where $Fc(t)$ is the fuel consumption of diesel generators at t-time, and E_f is an emission factor, which is dependent on the nature of the diesel generator and fuel.

B. DECISION VARIABLES

As mentioned earlier, the objective functions include the annualized costs of the system (ACS), the loss of power supply probability (LPSP), and the fuel emissions during one year. The decision variables are described as follows:

$$D = [D_{pv}, D_{wg}, D_{bat}, D_{dg}, H_{wg}, \beta] \tag{17}$$

The decision variables include the photovoltaic panel count D_{pv}, the wind turbine count D_{wg}, the battery count D_{bat}, and the diesel generator count D_{dg}. In addition, the slope angle of the pv board is β. Furthermore, the influence of the wind tower height H_{wg} on the simulation results is also considered.

Considering the constraints of the decision variables and the objectives mentioned above, the multi-objective optimization problem can be expressed as follows.

$$MinFj = (ACS, LPSP, F_e) \tag{18}$$

Subject to

$$\begin{aligned} (D_{pv}, D_{wg}, D_{bat}, D_{dg}) &\geq 0 \\ H_{low} \leq H_{wg} &\leq H_{high} \\ 0^\circ \leq \beta &\leq 90^\circ \end{aligned} \tag{19}$$

where F_j is the objective function; D_{pv},D_{wg},D_{bat}, and D_{dg} are integers; and H_{wg} is within a given height range. In addition, the maximum values for D_{pv}, D_{wg}, D_{bat}, D_{dg} are set to 30, 20, 30, 10, respectively.

IV. THE RELATED ALGORITHM

A. MULTI-OBJECTIVE OPTIMIZATION

HRES programming is usually a multi-objective optimization problem in which more than one objective is involved. That is, it is impossible to simultaneously achieve multiple optimal values for multiple sub-objects, and it is only possible to coordinate and form compromises between them so that each sub-goal is optimized as much as possible [19]. The essential difference between it and the single-objective optimization problem is that the solution is not unique, but there is a set of optimal solutions consisting of many Pareto optimal solutions. Each element in the set is called the Pareto optimal solution [4], as shown in Fig. 4. That is, between two solutions with differing non-domination ranks we prefer the point with the lower rank.

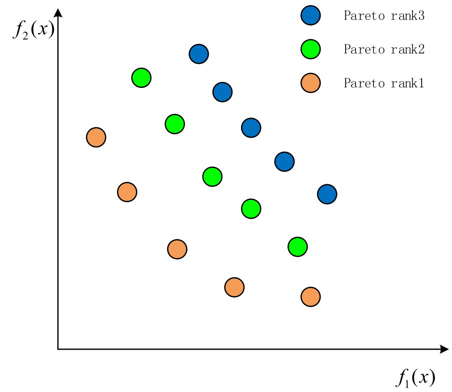


FIGURE 4. Pareto dominance level.

The multi-objective optimization problem is described in text as having D decision variable parameters, n objective functions, and $m + n$ constraints to form an optimization problem, the decision variables and the objective functions; and the constraints are functional relationships [18]. In the non-inferior solution, the decision-maker can only choose a non-inferior solution that satisfies the specific problem as the final solution. The mathematical form of the multi-objective optimization problem can be described as follows.

Definition 1: Multi-objective optimization problem

$$\begin{aligned} &\min y = f(x) = [f_1(x), f_2(x), \ldots, f_n(x)] \\ &s.t. x \in \Omega \end{aligned} \tag{20}$$

$F(x)$ is the multi-objective optimization, where $f_1(x), \ldots, f_n(x)$ are the target components and m is the number of targets.

Definition 2: Pareto Dominance

N minimizes the optimization problem when $h \in \{1, 2, \ldots, m\}, f_h(x) \leq f_h(y)$,

$j \in \{1, 2, \ldots, m\}$, and $f_h(x) < f_j(y)$. We indicate x control of y, as $x \prec y$.

Definition 3: Pareto Set

Take a multi-objective optimization problem for a given set of optimal solutions; if the solutions in the set are mutually dominant, that is, if the two are not dominant, then the solution set is called the Pareto set.

B. BRAINSTORMING OPTIMIZATION

During recently years, the BSO algorithm has been applied for many types of optimization problems, especially for the multi-objective optimization problems. BSO refers to bringing people together to brainstorm problems that are difficult for one person to solve. Brainstorming creates inspiration for solving problems. The core ideas are postponing judgment,

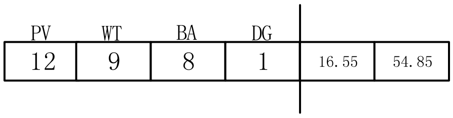


FIGURE 5. Coding of an individual solution.

bold hypotheses, cross-referencing and winning by quantity. Through a large number of assumptions, ultimately, it is greatly possible to produce an excellent problem solution, and the algorithm has achieved good results in optimizing test functions. This new algorithm combines the advantages of the group intelligent optimization algorithm and data mining. Each solution in the intelligent optimization algorithm is regarded as a data point. By clustering the data points, the optimal solution of the problem is found [85].

C. K-MEANS ALGORITHM

Clustering is an algorithm that classifies or packets data according to attributes or feature objects. The goal of this kind of algorithm is to cluster the objects that are close to each other, thus obtaining compact and independent clusters. The K-Means clustering algorithm is one of the most classical algorithms. As an important branch of data mining, the K-Means clustering algorithm is simple [86], easy to implement and extend, and can give full play to the advantages of large data sets. In this subsection, K-Means clustering method is adapted to the HRES problem. The K-Means clustering method is shown as follows.

The default of K-Means clustering is that the Euclidean distance is used to measure the distance. In this article, the method of measuring the distance is the distance of a city block, which is also called the L1-distance. The distance of a city block is the sum of the absolute wheelbases in the standard coordinate system, and the result is the total absolute values of the two coordinate differences. The distance between two n-dimensional vectors $(z_1, z_2, z_3, \ldots, z_n)$ and $(q_1, q_2, q_3, \ldots, q_n)$ should be expressed as follows:

$$d(z, q) = \sum_{j=1}^{p} |z_j - q_j| \tag{21}$$

Each cluster in the partition is defined by its member objects and by its centroid, or center. The centroid for each cluster is the point to which the sum of distances from all objects in that cluster is minimized.

V. THE PROPOSED ALGORITHM

The encoding is a floating-point encoding method, which must ensure that the genetic value is within a given interval limit. The crossover, mutation and other genetic operators that are used in the evolutionary algorithm must also confirm that the genetic value of the new individual that is generated by its results is also within this range limit. There are 6 genes on each chromosome. Thus, the first four decision variables are integers, and the latter two are real numbers, as shown below:

The above picture shows a kind of coding scheme corresponding to the 12 *PV* panels, 9 sets of wind turbines, 8 batteries and 8 diesel generators. The installation height of the fan is 16.55 meters, while the installation angle of the solar photovoltaic panels is 54.85 degrees.

The specific description of the BSO algorithm is as follows.

The flow chart for brainstorming optimizations is shown in Fig. 6.

Algorithm 1 K-Means Cluster

Input	The number of objects and clusters in the database	
Output	The square error criterion that is the minimum of k clusters	
1	K objects are arbitrarily selected from n data objects as the initial cluster center.	
2	repeat	
3		Each point is assigned to the nearest centroid to form k clusters
4		Recalculate the center of the mass of each cluster
5	Until the cluster does not change or the maximum number of iterations is reached	

The optimization algorithm of brainstorming mainly consists of two modules: the generic module and the study module. In the generic module adopt the Algorithm 1. The algorithm optimizes the information content by learning all kinds of information to drive the local search. Through the in-class mutual coordination and the mutation operation, it allows the algorithm to break through the local optimum to promote the global research. The cluster center's optimization procedure guarantees the algorithm's convergence performance. The process of optimizing the information variation ensures the diversity of the algorithm's population.

In the BSO, the interlace operation can be taken from line 14 of the BSO algorithm's description. P_b is the probability of updating the individual in the two ways and $r2$ is a number between 0 and 1 that is randomly generated.

There are four ways to update individuals in the BSO algorithm, which could be divided into the following two classifications. Fig. 7 (a) shows a class-center or a class-individual forming the new individual new through mutation. Fig. 7 (b) illustrates the two class-centers or class-individuals forming an old one through fusing. The old could generate the new through mutation. old1 and old2 are two different class-centers or class-individuals.

The probability of selecting the sub-group of each class is in direct proportion to the amount of individuals in the group. The stochastic disturbance can be expressed by the following formula:

$$X_N = X_S + \xi \cdot n(\mu, \sigma) \tag{22}$$

$$\gamma = \log((0.5 * m\_i - c\_i)/k) * r() \tag{23}$$

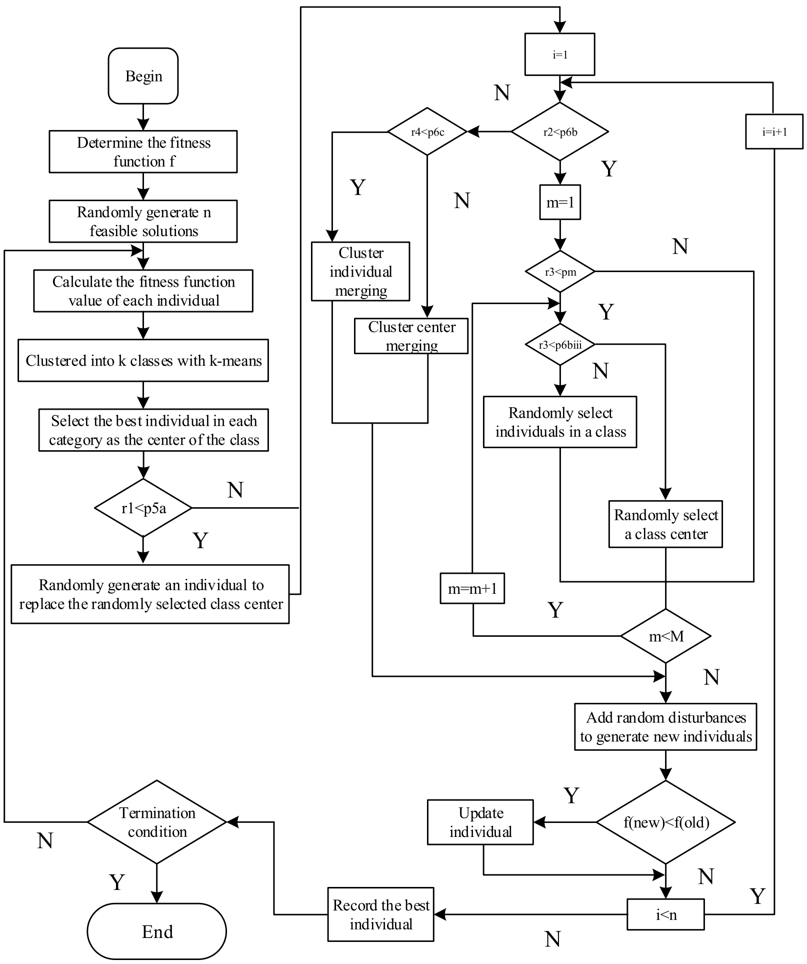


FIGURE 6. Proposed BSO framework.

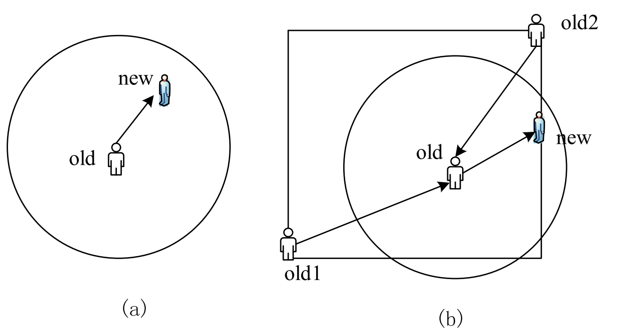


FIGURE 7. New individual generation mode.

In addition, X_N is the value of the dth dimension, X_S is the value of the dth dimension of the selected individual, $n(\mu, \sigma)$ is the Gaussian function with the mean of μ and the variance of σ, and γ is a weight coefficient that can be described by Formula (22). In addition, log() is log-sigmoid transfer function, m_i is the maximum number of iterations, c_i is the current iteration, k can alter the slope of the log() function and $rand()$ is a random value within (0, 1) [87].

The integration of two individuals is as follows:

$$x_e = tx_1 + (1 - t)x_2 \tag{24}$$

In addition, x_e is the new individual that is generated by two individuals' integration, x_1 and x_2 are the two individuals for implementing the integration operation and t is a random number between 0 and 1.

VI. SIMULATION AND RESULTS

A. EXPERIMENTAL INSTANCES

In this paper, a hybrid renewable energy generation system is adopted to supply electricity to the northeast of Zaragoza, Spain. Since different components make up different hybrid energy systems, different optimization schemes can be obtained when optimizing the model.

In this paper, the improved BSO algorithm is used to optimize the system by using the model proposed by Wang et al [26]. We obtain the local average wind speed, light intensity, temperature and other data from the local weather station. The simulation process of the system optimization is conducted using an hour step size, and so the experimental

Algorithm 2 Pseudo-Code of the Proposed Cooperative BSO With K-Means Algorithm

```
Randomly generate n potential solutions(x1,x2,...,xn).
Adjust all xi, i=1,2,...,n by one iteration of algorithm1
repeat
    Cluster n solutions into m clusters.
    Rank the solutions in each cluster and set the best one as the cluster center.
    Randomly generate a value r between 0 and 1.
    if r<p5a then
        Randomly select a cluster center
        Randomly generate an individual to replace the selected cluster
        Adjust the obtained solution by one iteration of algorithm1
    end of
    repeat
        Randomly generate a value r between 0 and 1.
        if r<p6b then
            Randomly select a cluster with probability p6bi.
            Randomly generate a value r1 between 0 and 1.
            if r1<p6bii then
            Select the cluster center and add random values to it to generate a new individual.
            else
            randomly select a solution from the chosen cluster and add a random value to the solution to generate a new one
            end if
            adjust the obtained solution by one iteration of the K-Means algorithm
        else
            Randomly select two clusters.
            generate a random value r2 between 0 and 1
            if r2<p6c then
                Two cluster centers are combined to generate a new individual
            else
            Two solutions from each selected cluster are randomly chosen to be combined to generate a new individual.
            end if
            Adjust the obtained solution by one iteration of algorithm1
        end if
        The newly generated solution is compared with the same solution index and the better one is kept
    Until n new solution is generated.
Until maximal iteration number is reached.
return the best solution among all population
```

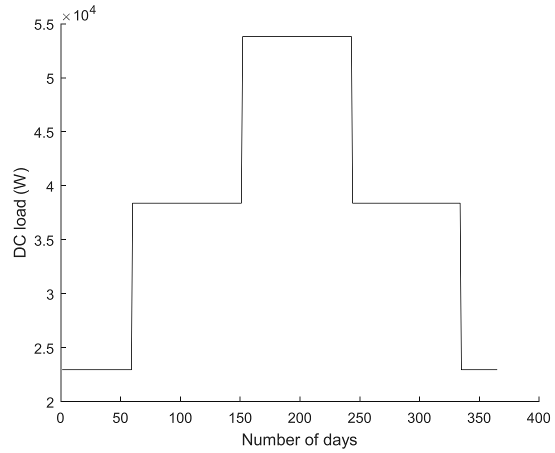


FIGURE 8. One year load demand.

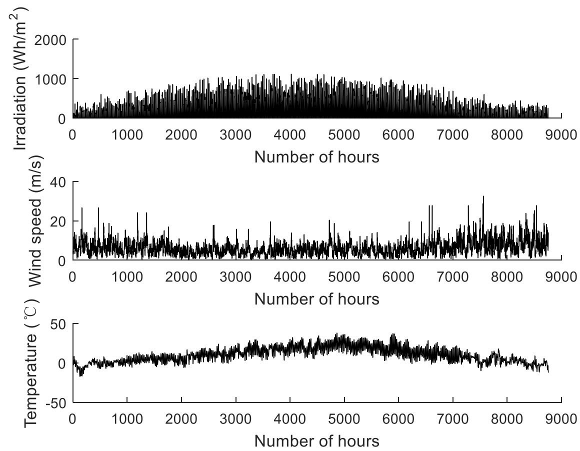


FIGURE 9. Hourly mean values of meteorological conditions.

data such as the solar radiation, wind speed, ambient temperature and load demand are calculated on an hourly basis, assuming that these data are measured every hour. For the sake of research, it is assumed that the load requirement of the hybrid renewable energy system is a branch load, and the branch voltage of the hybrid renewable energy and battery energy storage system is 48 V. The distribution of the daily load requirements in the region is as follows.

Input meteorological data include: horizontal plane solar radiation, average wind speed of 10 meters per hour and average environment temperature per hour.

B. EXPERIMENTAL PARAMETERS

In addition to the meteorological data and the load data, the input data of the system simulation and optimization process also include the technical parameters of each component and the related cost data. According to the related literatures, the output voltage and current, the maximum output voltage and current and the maximum output power of each component of the system can be determined under the standard test conditions. The initial investment costs *Cinv*,

TABLE 1. Solar photovoltaic panel parameters.

V_{oc}(V)	I_{sc}(A)	V_{max}(V)	I_{max}(A)	NCOT(°C)	C_{in}($)	C_{om}($)	Lifetime(year)
21	7.22	17	6.47	43	3000	30	25

TABLE 2. Parameters of the wind generator.

Rated power(W)	H_{low}(m)	H_{high}(m)	C_{in}($)	C_{om}($)	Tower C_{inv}($)	Tower C_{om}($)	Lifetime(year)
10000	5	30	3013	50	250	2.5	25

TABLE 3. Battery parameters.

Nominal capacity(Ah)	Voltage(V)	DOD(V)	Cinv($)	Com($)	Crep($)	Lifetime(year)
100	12	80	126	1.26	126	25

TABLE 4. Parameters of the Diesel Generator.

Rated power(W)	C_{inv}($)	C_{om}($)	Lifetime(year)
2000	1514	0.17	25

and maintenance costs *Com*, and other parameters are also incorporated.

The experimental parameters are shown in the following table. Table 1 lists the relevant property parameters of the photovoltaic panel. Table 2 shows the fan related parameters, including rated power, minimum and maximum installation height, initial investment cost, maintenance cost, investment cost and the maintenance cost of the fan tower, which are calculated separately. The property parameters of the battery, shown in Table 3, include the rated capacity, the rated voltage, and the maximum discharge depth. The costs of these property parameters include the investment cost, the maintenance cost, and the replacement cost. Table 4 demonstrates the relevant parameters of the diesel generator. The service life of these system components is 25 years except that the battery is 5 years. The additional components such as a photovoltaic plate, fan, and diesel generator are all set to 25 years. The life cycle of the system is also set to 25 years.

The parameters of the BSO algorithm are given in Table 5, where n_p is the population size, n_d is the dimension value of decision variables, and n_c is the size of clustering. The maximum number of iterations is 50.

C. EFFECTIVENESS OF THE SEQUENCE METHOD

Because of the complexity of the model and the diversity of the parameters, it is difficult to solve this kind of problem. As a new swarm intelligence optimization algorithm, the brainstorm optimization algorithm can solve this problem very well. First, 50 candidate solution populations were initialized and the fitness values of 50 individuals were calculated using the brainstorming optimization algorithm.

The clustering algorithm and the solution set converged to two clusters. We present an example. As shown in Table 6, we divided 6 individuals into two clusters. *Cluster_1* and *cluster_2* are used to represent the two clusters. *N* is the label of the individual, *C* is the cluster classification, and the individual {*1.5.6*} belongs to *cluster_1* with K-Means. The individual {*3.4.6*} belongs to *cluster_2*.

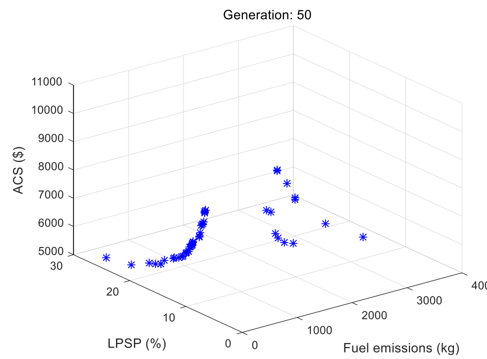


FIGURE 10. Fifty iterations result in a three-dimensional Pareto front.

In the brainstorming optimization algorithm, a new solution is generated by the combination of one solution or two solutions in the cluster. By comparing the newly generated solution with the same number of original solutions, we store the solution with the best adaptive value and enter the iteration as a new solution. After the iterations, all solutions are clustered into a small search area. The probabilistic parameters are used to control the probability of replacing the clustering centers with random solutions, to prevent the algorithm from converging prematurely and to avoid local extremum. After 50 iterations, the weight target value is unchanged. Three objectives values are visualized, as shown in Figs. 10-11.

It can be seen from the Pareto front of Fig. 12 that the annualized cost of the system (ACS) objective is negatively correlated with the loss of power supply probability (LPSP) and the fuel emissions objectives. Combined with the two-dimensional Pareto frontier below, we can see that reducing the system's fuel emissions would make the system more expensive, while the same reduction in the LPSP would result in a higher ACS value. In short, a system with higher

TABLE 5. BSO parameters.

n_p	n_d	n_c	P_{5a}	P_{6b}	P_{6biii}	P_{6c}	Max_iteration	μ	δ
50	6	2	0.2	0.8	0.4	0.5	50	0	1

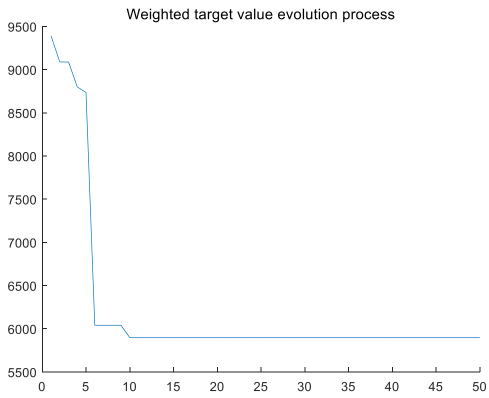


FIGURE 11. Weighted target value evolutionary process.

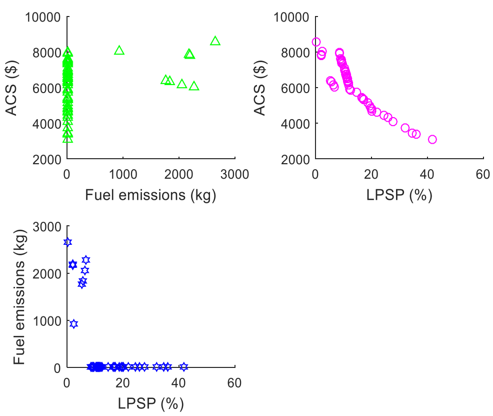


FIGURE 12. Two-dimensional Pareto fronts.

reliability and lower fuel emissions would be more costly. Therefore, an optimal system configuration scenario would make a trade-off between the three available goals, and none of them could be simultaneously minimized.

D. PARAMETER ANALYSIS

The BSO generally involves the following four parameters $p_{5a}, p_{6b}, p_{6biii}$ and p_{6c}. p_{5a} is the probability to decide whether to change the cluster center. p_{6b} is the probability to select parent solutions to generate new solutions from one or two clusters. p_{6biii} is the probability to decide whether to select the cluster center or to select a non-center solution randomly. p_{6c} is the probability to decide whether to select one cluster center or to select two cluster centers to generate a new solution.

E. EFFECTIVENESS OF THE SEQUENCE METHOD

Policymakers want the lowest costs, highest reliability, and as few contaminants as possible. To be able to measure the

TABLE 6. Optimization algorithm parameters of brain storming.

N	D_{pv}	D_{wg}	D_{bat}	D_{dg}	H_{wg}	β	C
1	20	6	29	0	15.13	55.44	1
2	12	7	24	1	12.12	42.33	2
3	11	10	27	3	12.22	43.50	2
4	18	7	26	1	15.07	54.48	2
5	19	8	28	0	14.79	56.28	1
6	17	7	29	0	14.26	56.01	1

pros and cons of each individual, a comprehensive indicator is used as the objective value. We select 10 solutions from the Pareto solution, and the corresponding decision variables are shown in the table below.

When the value of $Fe\ (kg)$ is 0, it means that the diesel generator is not used in this solution, that is, the value of D_{bat} is 0.

Solution 1 represents $D_{pv} = 11$, $D_{wg} = 5$, $D_{bat} = 19$, $D_{dg} = 1$, $H_{wg} = 12.12$, and $\beta = 59.03$. The three objectives values that are obtained are $F_e(kg) = 2265.52$, $LPSP = 6.78\%$, and $ACS = 6191.84\$$.

Solution 8 represents $D_{pv} = 25$, $D_{wg} = 10$, $D_{bat} = 30$, $D_{dg} = 0$, $H_{wg} = 12.38$, and $\beta = 74.50$. The three objectives values that are obtained are $F_e(kg) = 0$, $LPSP = 3.81\%$, and $ACS = 9683.33$.

Solution 10 represents $D_{pv} = 5$, $D_{wg} = 8$, $D_{bat} = 14$, $D_{dg} = 0$, $H_{wg} = 9.17$, and $\beta = 49.19$. The three objectives values that are obtained are $F_e(kg) = 0$, $LPSP = 28.31\%$, and $ACS = 4199.20$ \$.

Comparatively speaking, solution 8 is more stable than solution 1 and does not emit carbon dioxide and other gases, but the ACS value of solution 8 is higher. The greenhouse gas emissions of Solution8 are the same as those of Solution10, and Solution8 has higher system stability. The system annual costs of Solution10 are lower. Therefore, while pursuing the maximum stability of the system, the costs of the system are also increasing.

To verify the validity of the model, a time series simulation is carried out for one year with the time unit as an example, and the operation of each component of the system is observed. In the process, the batteries, solar panels, wind turbines, renewable energy loads and diesel generators are shown in Figs. 13-17:

In this paper, we apply the BSO algorithm to the HRES and optimize the annualized costs of the system (ACS), the loss of power supply probability (LPSP) and the total fuel emissions. Compared with the SPEA method [88], the two use different

TABLE 7. Solution set.

Solution	D_{pv}	D_{wg}	D_{bat}	D_{dg}	H_{wg}	β	F_e (kg)	LPSP (%)	ACS($)
1	11	5	19	1	12.12	59.03	2265.52	6.78	6191.84
2	20	7	27	0	16.61	53.30	0	6.63	7891.67
3	10	7	16	2	11.53	60.7	3180.70	2.43	7453.38
4	14	6	22	0	13.18	52.15	0	15.90	5816.48
5	19	7	28	0	15.78	54.31	0	7.32	7645.64
6	24	11	30	0	12.13	73.20	0	3.72	9840.26
7	10	8	16	3	11.08	61.63	3737.49	0	8400.37
8	25	10	30	0	12.38	74.50	0	3.81	9668.33
9	11	8	18	2	12.04	59.87	2542.97	2.10	7720.74
10	5	8	14	0	9.17	49.19	0	28.31	4199.20

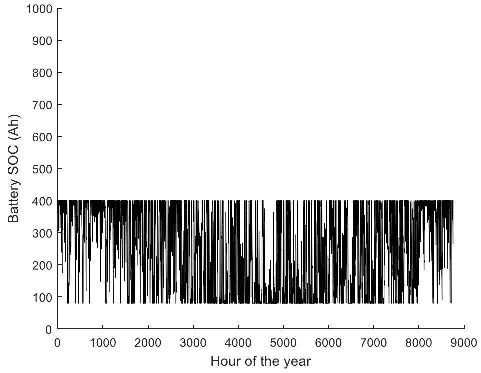


FIGURE 13. Battery bank SOC.

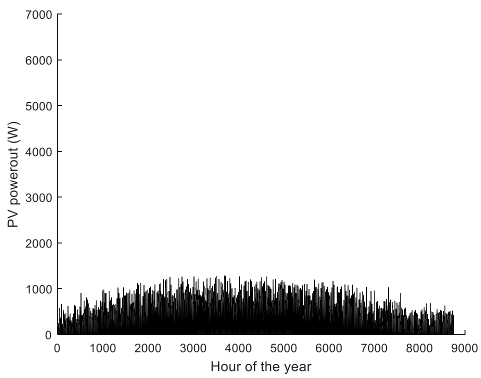


FIGURE 14. PV power output.

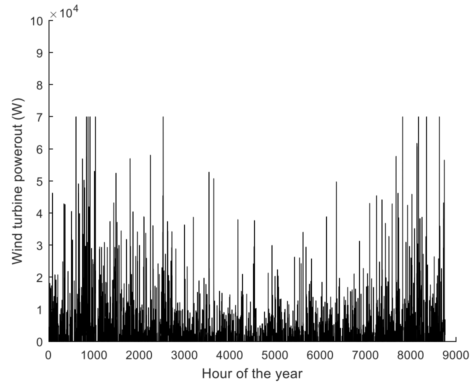


FIGURE 15. Wind turbine power output.

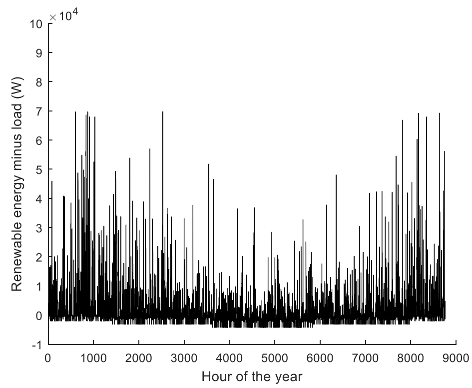


FIGURE 16. Renewable energy minus load.

components, and SPEA has more complex system components. Nevertheless, in a 3D coordinate system, the brainstorming algorithm has better diversity and a similar solution for the same classification. Compared with the PICEA [89], the convergence speed of the BSO algorithm is faster, and the optimal Pareto solution is found in a short time. The probabilistic parameters are used to control the probability of replacing clustering centers with random solutions to prevent the algorithm from converging prematurely and to avoid local extremum. Diesel generators and batteries were used more frequently in the study. The output power of the solar photovoltaic panels is higher in the summer and lowers in the winter, while the output power of the wind turbine is higher in the spring and autumn and lower in the winter and summer. Therefore, the system is susceptible to weather and other factors, which increases the uncertainty. Based on the analysis of the uncertain factors, this paper presents different system models with different system compositions, which provide more suitable solutions for decision makers.

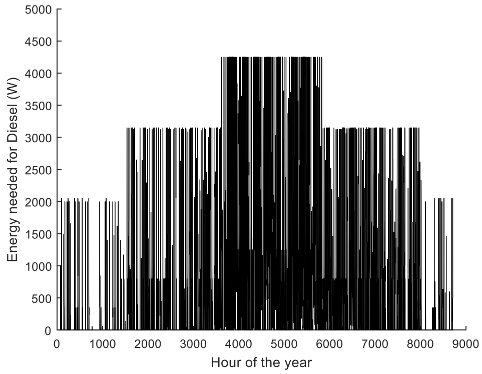


FIGURE 17. **Diesel energy needed.**

VII. CONCLUSIONS

In this paper, the optimal allocation problem of each component in a hybrid renewable energy system is studied, and the three objectives functions of the problem are the minimization of the annualized costs of the system (ACS), the loss of power supply probability (LPSP) and the total fuel emissions. An improved BSO is proposed. The K-Means clustering method is used to solve this problem, which makes the same clusters have similar solutions. By using the distance of a city block as the distance measure, the clustering of individuals is calculated and the solution is made feasible. To measure the merits and demerits of each individual, we take the composite index as the target value. In addition, to improve the efficiency of the algorithm, a unique crossover mutation strategy is adopted in the BSO. A group of Pareto optimal solutions are quickly obtained and introduced into the model to verify the validity of the model and the competitiveness of the algorithm.

Our future work will mainly focus on the following aspects: (1) Application of the BSO algorithm to large-scale problems to solve the problem of a large amount of data analysis. New measures are needed to improve the efficiency of the algorithm. (2) The current hybrid energy systems are uncertain in the deterministic environment and the future can be considered to be under the constraints of the uncertain environment. We will also consider designing a more complex renewable energy system.

REFERENCES

[1] M. D. A. Al-Falahi, S. D. G. Jayasinghe, and H. Enshaei, "A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system," *Energy Convers. Manage.*, vol. 143, pp. 252–274, Jul. 2017.

[2] P. Bajpai and V. Dash, "Hybrid renewable energy systems for power generation in stand-alone applications: A review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 2926–2939, 2012.

[3] J. B. Agustín and R. Dufo-López, "Simulation and optimization of stand-alone hybrid renewable energy systems," *Renew. Sustain. Energy Rev.*, vol. 13, no. 8, pp. 2111–2118, 2009.

[4] M. Fadaee and M. A. M. Radzi, "Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 3364–3369, 2012.

[5] V. Khare, S. Nema, and P. Baredar, "Solar-wind hybrid renewable energy system: A review," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 23–33, May 2016.

[6] Y. S. Mohammed, M. W. Mustafa, and N. Bashir, "Hybrid renewable energy systems for off-grid electric power: Review of substantial issues," *Renew. Sustain. Energy Rev.*, vol. 35, pp. 527–539, Jul. 2014.

[7] K. S. Krishna and K. S. Kumar, "A review on hybrid renewable energy systems," *Renew. Sustain. Energy Rev.*, vol. 52, pp. 907–916, Dec. 2015.

[8] R. Siddaiah and R. P. Saini, "A review on planning, configurations, modeling and optimization techniques of hybrid renewable energy systems for off grid applications," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 376–396, May 2016.

[9] T. Tezer, R. Yaman, and G. Yaman, "Evaluation of approaches used for optimization of stand-alone hybrid renewable energy systems," *Renew. Sustain. Energy Rev.*, vol. 73, pp. 840–853, Jun. 2017.

[10] L. M. Halabi and S. Mekhilef, "Flexible hybrid renewable energy system design for a typical remote village located in tropical climate," *J. Cleaner Prod.*, vol. 177, pp. 908–924, Mar. 2018.

[11] L. Kuznia, B. Zeng, G. Centeno, and Z. Miao, "Stochastic optimization for power system configuration with renewable energy in remote areas," *Ann. Oper. Res.*, vol. 210, no. 1, pp. 411–432, 2013.

[12] A. Akella, M. P. Sharma, and R. P. Saini, "Optimum utilization of renewable energy sources in a remote area," *Renew. Sustain. Energy Rev.*, vol. 11, no. 5, pp. 894–908, 2007.

[13] R. Eke, O. Kara, and K. Ulgen, "Optimization of a wind/PV hybrid power generation system," *Int. J. Green. Energy.*, vol. 2, no. 1, pp. 57–63, 2005.

[14] R. Dufo-López, J. L. Bernal-Agustín, and J. Contreras, "Optimization of control strategies for stand-alone renewable energy systems with hydrogen storage," *Renew. Energy*, vol. 32, no. 7, pp. 1102–1126, 2007.

[15] G. C. Seeling-Hochmuth, "A combined optimisation concet for the design and operation strategy of hybrid-PV energy systems," *Sol. Energy*, vol. 61, no. 2, pp. 77–87, 2012.

[16] R. Dufo-López and J. L. Bernal-Agustín, "Design and control strategies of PV-Diesel systems using genetic algorithms," *Sol. Energy*, vol. 79, no. 1, pp. 33–46, 2005.

[17] H. X. Yang, W. Zhou, L. Lu, and Z. Fang, "Optimal sizing method for stand-alone hybrid solar-wind system with LPSP technology by using genetic algorithm," *Sol. Energy.*, vol. 82, no. 4, pp. 354–367, 2008.

[18] Y. A. Katsigiannis, P. S. Georgilakis, and E. S. Karapidakis, "Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables," *IET Renew. Power. Gener.*, vol. 4, no. 5, pp. 404–419, Sep. 2010.

[19] H. Bilil, G. Aniba, and M. Maaroufi, "Multiobjective optimization of renewable energy penetration rate in power systems," *Energy Procedia*, vol. 50, pp. 368–375, Jun. 2014.

[20] M. Trivedi, *Multi-Objective Generation Scheduling with Hybrid Energy Resources*. Clemson, South Carolina: Clemson Univ., 2007.

[21] H. Borhanazad, S. Mekhilef, V. G. Ganapathy, M. Modiri-Delshad, and A. Mirtaheri, "Optimization of micro-grid system using MOPSO," *Renew. Energy*, vol. 71, pp. 295–306, Nov. 2014.

[22] A. Kamjoo, A. Maheri, A. M. Dizqah, and G. A. Putrus, "Multi-objective design under uncertainties of hybrid renewable energy system using NSGA-II and chance constrained programming," *Int. J. Elect. Power Energy Syst.*, vol. 74, pp. 187–194, Jan. 2016.

[23] M. Ming, R. Wang, Y. Zha, and T. Zhang, "Multi-objective optimization of hybrid renewable energy system using an enhanced multi-objective evolutionary algorithm," *Energies*, vol. 10, no. 5, p. 674, 2017.

[24] S. Abedi, A. Alimardani, G. B. Gharehpetian, G. H. Riahy, and S. H. Hosseinian, "A comprehensive method for optimal power management and design of hybrid RES-based autonomous energy systems," *Renew. Sustain. Energy Rev.*, vol. 16, no. 3, pp. 1577–1587, 2012.

[25] B. O. Bilal, V. Sambou, P. A. Ndiaye, C. M. F. Kébé, and M. Ndongo, "Optimal design of a hybrid solar-wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP)," *Renew. Energy*, vol. 35, no. 10, pp. 2388–2390, 2010.

[26] Z. Shi, R. Wang, and T. Zhang, "Multi-objective optimal design of hybrid renewable energy systems using preference-inspired coevolutionary approach," *Sol. Energy*, vol. 118, pp. 96–106, Aug. 2015.

[27] C. Rubio-Maya, J. Uche-Marcuello, A. Martínez-Gracia, and A. A. Bayod-Rújula, "Design optimization of a polygeneration plant fuelled by natural gas and renewable energy sources" *Appl. Energy*, vol. 88, no. 2, pp. 449–457, 2011.

[28] J. Q. Li, S. C. Bai, P. Y. Duan, H. Y. Sang, Y. Y. Han, and Z. X. Zheng, "An improved artificial bee colony algorithm for addressing distributed flow shop with distance coefficient in a prefabricated system," *Int. J. Prod. Res.*, 2019. doi: 10.1080/00207543.2019.1571687.

[29] J. Q. Li, J. D. Wang, Q. K. Pan, and P. Y. Duan, "A hybrid artificial bee colony for optimizing a reverse logistics network system," *Soft Comput.*, vol. 21, no. 20, pp. 6001–6018, 2017.

[30] H. Liu, B. Xu, D. Lu, and G. Zhang, "A path planning approach for crowd evacuation in buildings based on improved artificial bee colony algorithm," *Appl. Soft Comput.*, vol. 68, pp. 360–376, Jul. 2018.

[31] J. Li, P. Duan, H. Sang, S. Wang, Z. Liu, and P. Duan, "An efficient optimization algorithm for resource-constrained steelmaking scheduling problems," *IEEE Access*, vol. 6, pp. 33883–33894, 2018.

[32] L. Wang, G. Zhou, Y. Xu, and M. Liu, "An enhanced Pareto-based artificial bee colony algorithm for the multi-objective flexible job-shop scheduling," *Int. J. Adv. Manuf. Technol.*, vol. 60, pp. 1111–1123, Jun. 2012.

[33] J.-Q. Li, Q.-K. Pan, and M. F. Tasgetiren, "A discrete artificial bee colony algorithm for the multi-objective flexible job-shop scheduling problem with maintenance activities," *Appl. Math. Model.*, vol. 38, no. 3, pp. 1111–1132, Feb. 2014.

[34] Y.-Y. Han, J. Liang, Q.-K. Pan, J.-Q. Li, H.-Y. Sang, and N. N. Cao, "Effective hybrid discrete artificial bee colony algorithms for the total flowtime minimization in the blocking flowshop problem," *Int. J. Adv. Manuf. Technol.*, vol. 67, nos. 1–4, pp. 397–414, 2013.

[35] J. Li and Q.-K. Pan, "Solving the large-scale hybrid flow shop scheduling problem with limited buffers by a hybrid artificial bee colony algorithm," *Inf. Sci.*, vol. 316, pp. 487–502, Sep. 2015.

[36] C. Hu, H. Liu, and P. Zhang, "Cooperative co-evolutionary artificial bee colony algorithm based on hierarchical communication model," *Chin. J. Electron.*, vol. 25, no. 3, pp. 570–576, May 2016.

[37] J.-Q. Li, Q.-K. Pan, and P.-Y. Duan, "An improved artificial bee colony algorithm for solving hybrid flexible flowshop with dynamic operation skipping," *IEEE Trans. Cybern.*, vol. 46, no. 6, pp. 1311–1324, Jun. 2016.

[38] R. Ruiz, Q.-K. Pan, and B. Naderi, "Iterated Greedy methods for the distributed permutation flowshop scheduling problem," *Omega*, vol. 83, pp. 213–222, Mar. 2019.

[39] J. Q. Li and Y. Han, "A hybrid multi-objective artificial bee colony algorithm for flexible task scheduling problems in cloud computing system," *Cluster Comput.*, pp. 1–24, 2019.

[40] L. Wang, G. Zhou, Y. Xu, and M. Liu, "A hybrid artificial bee colony algorithm for the fuzzy flexible job-shop scheduling problem," *Int. J. Prod. Res.*, vol. 51, no. 12, pp. 3593–3608, 2013.

[41] J.-Q. Li, P. Duan, J. Cao, X.-P. Lin, and Y.-Y. Han, "A hybrid Pareto-based tabu search for the distributed flexible job shop scheduling problem with E/T criteria," *IEEE Access*, vol. 6, pp. 58883–58897, 2018.

[42] Y. Xia and Z. Fu, "Improved tabu search algorithm for the open vehicle routing problem with soft time windows and satisfaction rate," *Cluster Comput.*, 2018, pp. 1–9.

[43] H.-Y. Sang *et al.*, "Effective invasive weed optimization algorithms for distributed assembly permutation flowshop problem with total flowtime criterion," *Swarm Evol. Comput.*, vol. 44, pp. 64–73, Feb. 2019.

[44] J. Li, Q. Pan, and S. Xie, "An effective shuffled frog-leaping algorithm for multi-objective flexible job shop scheduling problems," *Appl. Math. Comput.*, vol. 218, no. 18, pp. 9353–9371, 2012.

[45] J.-Q. Li, Q.-K. Pan, P. N. Suganthan, and T. J. Chua, "A hybrid tabu search algorithm with an efficient neighborhood structure for the flexible job shop scheduling problem," *Int. J. Adv. Manuf. Technol.*, vol. 52, nos. 5–8, pp. 683–697, Feb. 2011.

[46] Q.-K. Pan and R. Ruiz, "Local search methods for the flowshop scheduling problem with flowtime minimization," *Eur. J. Oper. Res.*, vol. 222, no. 1, pp. 31–43, 2012.

[47] J.-Q. Li, Q.-K. Pan, and Y.-C. Liang, "An effective hybrid tabu search algorithm for multi-objective flexible job-shop scheduling problems," *Comput. Ind. Eng.*, vol. 59, no. 4, pp. 647–662, 2010.

[48] A. Baniamerian, M. Bashiri, and F. Zabihi, "Two phase genetic algorithm for vehicle routing and scheduling problem with cross-docking and time windows considering customer satisfaction," *J. Ind. Eng. Int.*, vol. 14, no. 1, pp. 15–30, 2018.

[49] K. Ghoseiri and S. F. Ghannadpour, "Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm," *Appl. Soft. Comput.*, vol. 10, no. 4, pp. 1096–1107, 2010.

[50] P.-Y. Duan, J.-Q. Li, Y. Wang, H.-Y. Sang, and B.-X. Jia, "Solving chiller loading optimization problems using an improved teaching-learning-based optimization algorithm," *Optim. Control Appl. Methods*, vol. 39, no. 1, pp. 65–77, 2018.

[51] J.-Q. Li, Q.-K. Pan, and K. Mao, "A discrete teaching-learning-based optimisation algorithm for realistic flowshop rescheduling problems," *Eng. Appl. Artif. Intell.*, vol. 37, pp. 279–292, Jan. 2015.

[52] Z. Zheng and J. Li, "Optimal chiller loading by improved invasive weed optimization algorithm for reducing energy consumption," *Energy Buildings*, vol. 161, pp. 80–88, Feb. 2018.

[53] Y. Liu, Y.-C. Jiao, Y.-M. Zhang, and Y.-Y. Tan, "Synthesis of phase-only reconfigurable linear arrays using multiobjective invasive weed optimization based on decomposition," *Int. J. Antennas Propag.*, vol. 2014, Aug. 2014, Art. no. 630529.

[54] H.-Y. Sang, Q.-K. Pan, P.-Y. Duan, and J.-Q. Li, "An effective discrete invasive weed optimization algorithm for lot-streaming flowshop scheduling problems," *J. Intell. Manuf.*, vol. 29, no. 6, pp. 1337–1349, 2018.

[55] Y.-H. Jia *et al.*, "A dynamic logistic dispatching system with set-based particle swarm optimization," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 9, pp. 1607–1621, Sep. 2018.

[56] H. Liu, L. Gao, and Q. Pan, "A hybrid particle swarm optimization with estimation of distribution algorithm for solving permutation flowshop scheduling problem," *Expert Syst. Appl.*, vol. 38, no. 4, pp. 4348–4360, Apr. 2011.

[57] J.-Q. Li, Q.-K. Pan, and K. Mao, "A hybrid fruit fly optimization algorithm for the realistic hybrid flowshop rescheduling problem in steelmaking systems," *IEEE Trans. Automat. Sci. Eng.*, vol. 13, no. 2, pp. 932–949, Apr. 2016.

[58] E. Osaba, X.-S. Yang, F. Diaz, E. Onieva, A. D. Masegosa, and A. Perallos, "A discrete firefly algorithm to solve a rich vehicle routing problem modelling a newspaper distribution system with recycling policy," *Soft Comput.*, vol. 21, no. 18, pp. 5295–5308, 2017.

[59] Q.-K. Pan, H.-Y. Sang, J.-H. Duan, and L. Gao, "An improved fruit fly optimization algorithm for continuous function optimization problems," *Knowl.-Based Syst.*, vol. 62, pp. 69–83, May 2014.

[60] T. Meng, Q.-K. Pan, J.-Q. Li, and H.-Y. Sang, "An improved migrating birds optimization for an integrated lot-streaming flow shop scheduling problem," *Swarm Evol. Comput.*, vol. 38, pp. 64–78, Feb. 2018.

[61] B. Zhang, Q.-K. Pan, X.-L. Zhang, and P.-Y. Duan, "An effective hybrid harmony search-based algorithm for solving multidimensional knapsack problems," *Appl. Soft Comput.*, vol. 29, pp. 288–297, Apr. 2015.

[62] Z.-X. Zheng, J.-Q. Li, and P.-Y. Duan, "Optimal chiller loading by improved artificial fish swarm algorithm for energy saving," *Math. Comput. Simul.*, vol. 155, pp. 227–243, Jan. 2019.

[63] W. Zheng, Y. Tan, L. Meng, and H. Zhang, "An improved MOEA/D design for many-objective optimization problems," *Appl. Intell.*, vol. 48, no. 10, pp. 3839–3861, 2018.

[64] X. Xu, Y. Tan, W. Zheng, and S. Li, "Memory-enhanced dynamic multi-objective evolutionary algorithm based on Lp decomposition," *Appl. Sci.*, vol. 8, no. 9, p. 1673, 2018.

[65] R. Han, Y. Gao, C. Wu, and D. Lu, "An effective multi-objective optimization algorithm for spectrum allocations in the cognitive-radio-based Internet of Things," *IEEE Access*, vol. 6, pp. 12858–12867, 2018.

[66] J.-Q. Li, H.-Y. Sang, Y.-Y. Han, C.-Q. Wang, and K.-Z. Gao, "Efficient multi-objective optimization algorithm for hybrid flow shop scheduling problems with setup energy consumptions," *J. Clean. Prod.*, vol. 181, pp. 584–598, Apr. 2018.

[67] A. K. Goswami, C. P. Gupta, and G. K. Singh, "Minimization of voltage sag induced financial losses in distribution systems using FACTS devices," *Electr. Power Syst. Res.*, vol. 81, no. 3, pp. 767–774, 2011.

[68] S. Gope, A. K. Goswami, P. K. Tiwari, and S. Deb, "Rescheduling of real power for congestion management with integration of pumped storage hydro unit using firefly algorithm," *Int. J. Elect. Power Energy Syst.*, vol. 83, pp. 434–442, Dec. 2016.

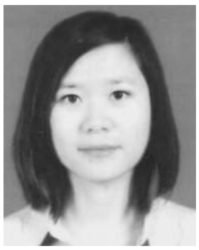
[69] Z. Liu, H. Xu, X. Zhao, P. Liu, and J. Li, "Multi-attribute group decision making based on intuitionistic uncertain linguistic hamy mean operators with linguistic scale functions and its application to health-care waste treatment technology selection," *IEEE Access*, vol. 7, pp. 20–46, 2018.

[70] B. Niu, H. Li, Z. Zhang, J. Li, T. Hayat, and F. E. Alsaadi, "Adaptive neural-network-based dynamic surface control for stochastic interconnected nonlinear nonstrict-feedback systems with dead zone," *IEEE Trans. Syst., Man, Cybern., Syst.*, to be published.

[71] J.-Q. Li, Q.-K. Pan, and K.-Z. Gao, "Pareto-based discrete artificial bee colony algorithm for multi-objective flexible job shop scheduling problems," *Int. J. Adv. Manuf. Technol.*, vol. 55, pp. 1159–1169, Aug. 2011.
[72] Y. Han, J.-Q. Li, D. Gong, and H. Sang, "Multi-objective migrating birds optimization algorithm for stochastic lot-streaming flow shop scheduling with blocking," *IEEE Access*, vol. 7, pp. 5946–5962, 2019.
[73] Y. Han, D. Gong, and X. Sun, "A discrete artificial bee colony algorithm incorporating differential evolution for the flow-shop scheduling problem with blocking," *Eng. Optimiz.*, vol. 47, no. 7, pp. 927–946, 2015.
[74] Y. Y. Han, D. W. Gong, J. Q. Li, and Y. Zhang, "Solving the blocking flow shop scheduling problem with makespan using a modified fruit fly optimisation algorithm," *Int. J. Prod. Res.*, vol. 54, no. 22, pp. 6782–6797, 2016.
[75] J. Wang, B. Gong, H. Liu, S. Li, and J. Yi, "Heterogeneous computing and grid scheduling with parallel biologically inspired hybrid heuristics," *Trans. Inst. Meas. Control*, vol. 36, no. 6, pp. 805–814, 2014.
[76] X.-W. Zheng, D.-J. Lu, X.-G. Wang, and H. Liu, "A cooperative coevolutionary biogeography-based optimizer," *Appl. Intell.*, vol. 43, no. 1, pp. 95–111, 2015.
[77] N. Pogaku, M. Prodanovic, and T. C. Green, "Modeling, analysis and testing of autonomous operation of an inverter-based microgrid," *IEEE Trans. Power Electron.*, vol. 22, no. 2, pp. 613–625, Mar. 2007.
[78] J. Bai and H. Liu, "Multi-objective artificial bee algorithm based on decomposition by PBI method," *Appl. Intell.*, vol. 45, no. 4, pp. 976–991, 2016.
[79] P. Zhang, H. Liu, and Y. Ding, "Dynamic bee colony algorithm based on multi-species co-evolution," *Appl. Intell.*, vol. 40, no. 3, pp. 427–440, 2014.
[80] H. Liu, P. Zhang, B. Hu, and P. Moore, "A novel approach to task assignment in a cooperative multi-agent design system," *Appl. Intell.*, vol. 43, no. 1, pp. 162–175, 2015.
[81] Z. Zhang and H. Liu, "Social recommendation model combining trust propagation and sequential behaviors," *Appl. Intell.*, vol. 43, no. 3, pp. 695–706, 2015.
[82] J. Wang, B. Gong, H. Liu, and S. Li, "Model and algorithm for heterogeneous scheduling integrated with energy-efficiency awareness," *Trans. Inst. Meas. Control*, vol. 38, no. 4, pp. 452–462, 2015.
[83] C. Li, J. Yi, H. Wang, G. Zhang, and J. Li, "Interval data driven construction of shadowed sets with application to linguistic word modelling," *Inf. Sci.*, to be published. doi: 10.1016/j.ins.2018.11.018.
[84] J. Wang, B. Gong, H. Liu, and S. Li, "Multidisciplinary approaches to artificial swarm intelligence for heterogeneous computing and cloud scheduling," *Appl. Intell.*, vol. 43, no. 3, pp. 662–675, Oct. 2015.
[85] Z. Jia, H. Duan, and Y. Shi, "Hybrid brain storm optimisation and simulated annealing algorithm for continuous optimisation problems," *Int. J. Bio-Inspired Comput.*, vol. 8, no. 2, pp. 109–121, 2016.
[86] A. Likas, N. Vlassis, and J. J. Verbeek, "The global k-means clustering algorithm," *Pattern Recognit.*, vol. 36, no. 2, pp. 451–461, Feb. 2003.
[87] S. Cheng, Q. Qin, J. Chen, and Y. Shi, "Brain storm optimization algorithm: A review," *Artif. Intell. Rev.*, vol. 46, no. 4, pp. 445–458, 2016.
[88] R. Dufo-López and J. L. Bernal-Agustín, "Multi-objective design of PV-winddiesel-hydrogenbattery systems," *Renew. Energy*, vol. 33, no. 12, pp. 2559–2572, Dec. 2008.
[89] R. Wang, R. C. Purshouse, and P. J. Fleming, "Preference-inspired coevolutionary algorithms for many-objective optimization," *IEEE Trans. Evol. Comput.*, vol. 17, no. 4, pp. 474–494, Aug. 2013.

XING-RUI CHEN received the B.Sc. degree from Shandong Normal University, in 2017, where he is currently pursuing the master's degree. His current research interests include discrete optimization and scheduling.

JUN-QING LI received the master's degree in computer science and technology from Shandong Economic University, Shandong, China, in 2004, and the Ph.D. degree from Northeastern University, Shenyang, China, in 2016. Since 2017, he has been with School of Information Science and Engineering, Shandong Normal University, where he became a Professor, in 2017. He is currently with the School of Computer Science, Liaocheng University. He is also with the Key Laboratory of Computer Network and Information Integration, Southeast University, Nanjing, China. He has authored more than 30 refereed papers. His current research interests include intelligent optimization and scheduling.



YUYAN HAN received the Ph.D. degree from the School of Control Science and Engineering, China Mining University, Xuzhou, China, in 2016. Since 2016, she has been a Lecturer with the School of Computer, Liaocheng University. She has authored more than 10 refereed papers. Her current research interests include discrete optimization and scheduling.

BEN NIU received the Ph.D. degree from the School of Information, Northeastern University, Shenyang, China, in 2013. Since 2018, he has been a Professor with the School of Information Science and Engineering, Shandong Normal University. He has authored more than 30 referred papers. His current research interests include nonlinear optimization algorithm.

LILI LIU received the Ph.D. degree from the School of Information Science and Engineering, Harbin Engineering University, Harbin, China, in 2017. Since 2017, she has been a lecturer with the School of Computer, Liaocheng University. She has authored more than 10 refereed papers. Her current research interests include discrete optimization and scheduling.

BIAO ZHANG received the Ph.D. degree from School of Mechanical Engineering, Huazhong University of Science and Technology, Wuhan, China, in 2019. Since 2019, he has been a lecturer with the School of Computer, Liaocheng University. He has authored more than 10 refereed papers. His current research interests include discrete optimization and scheduling.