Improved binary gaining-sharing knowledge-based algorithm with mutation for fault section location in distribution networks

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Abstract

Fault section location (FSL) plays a critical role in shortening blackout time and restoring power supply for distribution networks. This paper converts the FSL task into a binary optimization problem using the feeder terminal units (FTUs) information. The discrepancy between the reported overcurrent alarms and the expected overcurrent states of the FTUs is adopted as the objective function. It is a typical 0-1 combinatorial optimization problem with many local optima. An improved binary gaining-sharing knowledge-based algorithm (IBGSK) with mutation is proposed to effectively solve this challenging binary optimization problem. Since the original GSK cannot be applied in binary search space directly, and it is easy to get stuck in local optima, IBGSK encodes the individuals as binary vectors instead of real vectors. Moreover, an improved junior gaining and sharing phase and an improved senior gaining and sharing phase are designed to update individuals directly in binary search space. Furthermore, a binary mutation operator is presented and integrated into IBGSK to enhance its global search ability. The proposed algorithm is applied to two test systems, i.e., the IEEE 33-bus distribution network and the USA PG&E 69-bus distribution network. Simulation results indicate that IBGSK outperforms the other twelve advanced algorithms and the original GSK in solution quality, robustness, convergence speed, and statistics. It equilibrates the global search ability and the local search ability effectively. It can diagnose different fault scenarios with 100% and 99% success rates for these two test systems, respectively. Besides, the effect of mutation probability on IBGSK is also investigated, and the result suggests a moderate value. Overall, simulation results

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demonstrate that IBGSK shows highly promising potential for the FSL problem of distribution networks.

Keywords: distribution network, fault section location, gaining-sharing knowledge-based algorithm

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1. Introduction

Fault section location (FSL) is an indispensable supporting function of self-healing smart distribution networks [1]. Its primary purpose is to locate faulty section(s) and promote quick restoration [2-4]. Many feeder terminal units (FTUs) are installed in a distribution network to monitor the operating conditions. When a section suffers from a fault, the overcurrent information will be quickly acquired by related FTUs and then sent to the distribution management systems (DMS). Consequently, those collected alarm signals provided by the FTUs are available for locating this faulty section.

In the system operating process, there is the possibility that several sections of a distribution network may suffer from faults simultaneously. In this context, more alarm signals will pack into the DMS. However, some alarm signals may be lost or distorted during the information transmission process. Multiple faults and wrong signals collectively increase the difficulty of FSL. Hence, various methods have been introduced to improve the accuracy of FSL. For example, the authors in [5] employed algebraic-based Petri nets to model an inference net to locate the faults. The authors in [6] combined hierarchical fuzzy Petri nets with the time sequence of alarm information to improve the location correctness. The authors in [7] built a fuzzy Petri net model to use multiple sources to eliminate the possible false location. The authors in [8] used a Bayesian network to model the causality between the feeder state and the overcurrent information and then utilized a voting strategy to obtain the location decision. In [9], a spiking neural P system-based graphical reasoning location model was established to represent the FSL process. The authors in [10] proposed a regularized radial basis function neural network-based location method. In [11], the authors first decomposed the main transformer’s electric signals using optimized variational mode decomposition. They then employed a convolutional neural network to extract the eigenvectors of obtained decomposed modes to identify the fault(s). In [12], the authors adopted a signal-to-image algorithm to transform fault signals from the time domain to the image domain and then used a convolutional neural network to extract crucial information from the image domain to locate the fault(s). In [13], a matrix algorithm based on the system structure matrix and fault information matrix was designed to identify the faulty section(s). In [14], the authors used the voltage and current measured by smart meters in different parts of the distribution network to identify the faulty section(s). These methods mentioned above have pushed forward the rapid development of FSL.

However, they also have some shortcomings. For example, the graphical-based methods such as Petri nets, Bayesian network, and spiking neural P system are intuitive, but their fault tolerance is low. Although the fault tolerance of the neural network-based method is high, extracting and updating numerous training samples is not an easy task. Like the graphical-based methods, the matrix-based method is also unreliable if some FTUs' signals are wrong.

As an effective alternative for the FSL problem, the analytic model-based method is a simple yet reliable location approach. Methodologically, it works differently from the methods mentioned above. It converts the FSL task into a binary optimization problem which various optimization solvers can subsequently solve. It has the benefits of strict logic explanation, reasonable mathematical description, and easy implementation, and thus it gains increasing attention. Many optimization methods with diverse characteristics have been developed to solve the converting binary optimization problem. The metaheuristic algorithms have seemed to be an effective alternative to the classical methods and attracted more and more attention in solving practical complex optimization problems, including combinatorial and NP-hard problems [15, 16]. They are robust to the initial conditions and impose nothing on the problem formulation [17, 18]. Many metaheuristic algorithms and their variants have been put forward to the FSL problem of distribution networks. For example, to accelerate the convergence of the quantum genetic algorithm, gradient descent was adopted to dynamically adjust the rotation angle mechanism and quantum catastrophe [19]. In [20], a multiple-population strategy and a chaotic strategy were proposed to improve the global search ability of the genetic algorithm. The authors in [21] compared the optimization abilities of the ant colony algorithm and quantum genetic algorithm in solving the FSL problem and found that the quantum genetic algorithm is better than the ant colony algorithm with the increase of distortion information. The authors in [22] presented a binary particle swarm optimization for this concerning problem. In [23], a chaotic particle swarm optimization based on the chaos theory was introduced to achieve accurate and fast location results in the distribution network. In [24], a comprehensive learning method and a cooperative strategy were combined to equilibrate the global and local search in the quantum particle swarm optimization. The authors in [25] employed a minimum hitting set criterion to integrate the genetic algorithm and particle swarm optimization to improve the location efficiency and accuracy. In [26], a two-population evolution scheme was constructed to hybridize the particle swarm optimization with differential evolution to enhance the effectiveness of locating multiple faulty sections in a multi-source distribution network. To improve the accuracy of FSL for active distribution networks, the authors in [27] introduced the differential evolution to the wolf pack algorithm to enrich the population diversity and enhance global optimization. The authors in [28] combined the search step and iterations to improve the convergence speed of the cuckoo search algorithm. In [29], a sine and cosine optimization strategy was integrated to guide and update the position of individuals of gray wolf optimization to reduce the premature probability and improve the accuracy. In [30], an adaptive mutation factor was presented to solve the early convergence problem of the shuffled frog leaping algorithm. In [31], a fuzzy reasoning mechanism was established to respond to the own fitness of bats and thus modify their velocity factors to help the bat algorithm jump out of the local extremum. The authors in [32] adopted the chaos theory to improve the global search capability of the Jaya algorithm. In [33], the fruit fly optimization algorithm was introduced to demonstrate its effectiveness in solving the FSL problem of distribution networks.

These metaheuristic algorithms mentioned above have exerted a remarkable role in the progress of the FSL problem of distribution networks. Nonetheless, much remains to be done regarding the performance improvement of metaheuristic algorithms to refine their searching abilities because each algorithm has its advantages and disadvantages. For example, particle swarm optimization is easy to implement, but it has low search accuracy and easily falls into the local optimum [34]. The differential evolution has the advantages of solid robustness and fewer control parameters. However, its convergence is low in the late search stage [35]. Ant colony optimization takes on the characteristics of positive feedback, distributed computing, and strong robustness. Nevertheless, it also encounters the drawbacks of slow convergence, difficulty determining parameters, and premature convergence [36-38]. The Jaya algorithm is effective at exploitation, but it easily suffers from the problem of premature convergence [39].

In fact, following the no-free-launch theorem, more attempts are still necessary and desired. These motivate the authors to apply a newly presented algorithm called the gaining-sharing knowledge-based algorithm (GSK) for the FSL problem. GSK was invented by Ali Wagdy Mohamed et al. in 2020 [40] and is featured with simple structure, robustness, and easy implementation. It has been proven to be an effective and reliable metaheuristic algorithm for real-parameter benchmark optimization problems and some real-world optimization problems [41, 42].

GSK is a very young yet robust metaheuristic algorithm, and its application to the concerned FSL problem has not been reported. The original GSK was designed to solve optimization problems in continuous search space and thus could not be used for discrete optimization problems directly. In addition, similar to other metaheuristic algorithms, the original GSK also encounters some shortcomings. One of them is that it easily suffers from converging at local optima due to the lack of population diversity. To extend the application scope of GSK to binary search space and further enhance its performance in solving the FSL problem, this current research proposes several strategies to improve GSK from aspects of individual encoding, individual updating, and mutation. The main contributions are as follows:

(1) To the best of our knowledge, this is the first time that GSK is applied to the FSL problem of distribution networks. An improved variant of GSK called IBGSK is presented in binary search space by encoding individuals as binary vectors instead of real vectors.

(2) Improved junior gaining and sharing phase and improved senior gaining and sharing phase are designed to update individuals in binary search space.

(3) A binary mutation operator is developed and integrated into IBGSK to maintain population diversity and thus equilibrate the global search and local search abilities.

(4) The effectiveness of IBGSK is fully verified on different fault scenarios of the IEEE 33-bus distribution network and the USA PG&E 69-bus distribution network. Twelve advanced algorithms and the original GSK are employed to demonstrate its superiority. Besides, the effect of mutation probability on IBGSK is empirically investigated.

The rest of this paper is structured as follows. The mathematical model of FSL is provided in Section 2. Section 3 presents the proposed IBGSK and its implementation in the FSL problem of distribution networks. Section 4 provides the simulation results, while Section 5 summarizes this work.

2. Mathematical model formulation

When a fault occurs at a distribution network section, the fault currents will be monitored by the well-designed FTUs. Some related FTUs will detect the overcurrent greater than the corresponding preset values. This detected overcurrent information can be utilized to locate the faulty section, which is precisely the primary purpose of the FSL. The FSD can be expressed as a binary optimization problem [43, 44]:

$$\begin{aligned} &\min f(\boldsymbol{S}) \\ &s.t. \begin{cases} \boldsymbol{S} = [s_1, s_2, \ldots, s_D] \in Z^D \\ s_d = 0 \text{ or } 1, \quad d = 1, 2, \ldots, D \end{cases} \end{aligned} \tag{1}$$

where $\boldsymbol{S} = [s_1, s_2, \ldots, s_D]$ is a binary vector representing the fault states of D candidate faulty section(s). It is also the decision variable vector. If the ith section is faulty, then s_i equals 1; otherwise, it equals 0. The objective function $f(\boldsymbol{S})$ evaluates the difference between the detected overcurrent information I_i $(i = 1, 2, \ldots, Q)$ of Q FTUs and their expected current states I_i^*. It can be formulated as follows:

$$f(\boldsymbol{S}) = \sum_{i=1}^{Q} |I_i - I_i^*| + w \sum_{d=1}^{D} |s_d| \tag{2}$$

where $w \in (0, 1)$ is a weighting parameter.

The actual current state I_i is equal to 1 if the i-th FTU detects overcurrent; otherwise, it equals 0. If a section suffers from a fault, those FTUs located between this section and the power source will detect the overcurrent. Therefore, the expected current state I_i^* of ith FTU is equal to the logical OR operation of the fault states of all sections between the i-th FTU and the radial branch terminal, which is expressed as follows:

$$I_i^* = \vee s_{i,d} \tag{3}$$

3. IBGSK and its application for the FSL problem

3.1 Original GSK

GSK is a newly developed metaheuristic algorithm [40]. In GSK, a population with N individuals in the t-th iteration can be described as $\boldsymbol{Pop} = \{\boldsymbol{x}_1^t, \boldsymbol{x}_2^t, \cdots, \boldsymbol{x}_N^t\}$, $\boldsymbol{x}_i^t = [x_{i,1}^t, x_{i,2}^t, \ldots, x_{i,D}^t]$, $i = 1, 2, \ldots, N$. In each iteration, GSK sorts the individuals in ascending order according to the objective function values and then uses the junior gaining and sharing phase and the senior gaining and sharing phase to update the population individuals together.

3.1.1 Junior gaining and sharing phase

As shown in Eq. (4), a target individual $\boldsymbol{x}_i^t$ gains knowledge from its two adjacent individuals $\boldsymbol{x}_{i-1}^t$ and $\boldsymbol{x}_{i+1}^t$. Besides, it also shares knowledge from another mutually exclusive random individual $\boldsymbol{x}_r^t$.

$$\boldsymbol{x}_{\text{new},i}^t = \begin{cases} \boldsymbol{x}_i^t + k_f \cdot [(\boldsymbol{x}_{i-1}^t - \boldsymbol{x}_{i+1}^t) + (\boldsymbol{x}_r^t - \boldsymbol{x}_i^t)], & \text{if } f(\boldsymbol{x}_r^t) < f(\boldsymbol{x}_i^t) \\ \boldsymbol{x}_i^t + k_f \cdot [(\boldsymbol{x}_{i-1}^t - \boldsymbol{x}_{i+1}^t) + (\boldsymbol{x}_i^t - \boldsymbol{x}_r^t)], & \text{if } f(\boldsymbol{x}_r^t) \geq f(\boldsymbol{x}_i^t) \end{cases} \tag{4}$$

where $\boldsymbol{x}_{\text{new},i}^t$ is a trial vector for $\boldsymbol{x}_i^t$. $f(\cdot)$ is the objective function value. k_f (>0) is a knowledge factor.

Note that if the target individual is the best ($\boldsymbol{x}_1^t$), then the second-best ($\boldsymbol{x}_{i-1}^t$ is $\boldsymbol{x}_2^t$) and third-best ($\boldsymbol{x}_{i+1}^t$ is $\boldsymbol{x}_3^t$) individuals are chosen as its adjacent individuals. Similarly, if the target individual is the worst individual ($\boldsymbol{x}_N^t$), then the third last ($\boldsymbol{x}_{i-1}^t$ is $\boldsymbol{x}_{N-2}^t$) and second last ($\boldsymbol{x}_{i+1}^t$ is $\boldsymbol{x}_{N-1}^t$) individuals are chosen as its adjacent individuals.

3.1.2 Senior gaining sharing knowledge phase

The population is first classified into three levels during this phase: best, middle, and worst. The best level and the worst level each include $p \times N$ ($p \in [0,1]$) individuals, while the middle level has the rest $(1-2p) \times N$ individuals. Then for each target individual $\boldsymbol{x}_i^t$, it gains knowledge from three individuals of different groups using the following method:

$$\boldsymbol{x}_{\text{new},i}^t = \begin{cases} \boldsymbol{x}_i^t + k_f \cdot [(\boldsymbol{x}_{p-\text{best}}^t - \boldsymbol{x}_{p-\text{worst}}^t) + (\boldsymbol{x}_m^t - \boldsymbol{x}_i^t)], & \text{if } f(\boldsymbol{x}_m^t) < f(\boldsymbol{x}_i^t) \\ \boldsymbol{x}_i^t + k_f \cdot [(\boldsymbol{x}_{p-\text{best}}^t - \boldsymbol{x}_{p-\text{worst}}^t) + (\boldsymbol{x}_i^t - \boldsymbol{x}_m^t)], & \text{if } f(\boldsymbol{x}_m^t) \geq f(\boldsymbol{x}_i^t) \end{cases} \tag{5}$$

where $\boldsymbol{x}^t_{p\text{-best}}$, $\boldsymbol{x}^t_{p\text{-worst}}$ and $\boldsymbol{x}^t_m$ denote random individuals selected from the best, middle, and worst levels, respectively.

In GSK, both phases are used to update different dimensions of an individual. The numbers of dimensions that undergo the junior phase and the senior phase are calculated by the following formulation, respectively:

$$D_{\text{jp}} = (1 - t / t_{\max})^K \times D \tag{6}$$

$$D_{\text{sp}} = D - D_{\text{jp}} \tag{7}$$

where K is a knowledge rate, and $t_{\max}$ is the maximum number of iterations.

Algorithm 1 presents the pseudocode of GSK. k_r ($\in[0,1]$) is a knowledge ratio used to reserve the inherited knowledge from the target individual. After generating the trial vector $\boldsymbol{x}^t_{\text{new},i}$, $\boldsymbol{x}^t_{\text{new},i}$ and $\boldsymbol{x}^t_i$ will compete to survive to the next iteration according to their objective function values.

Algorithm 1: The main procedure of GSK

Generate a random initial population ***Pop***
Evaluate the fitness for each individual
Initialize the iteration counter $t = 1$
While the stopping condition is not satisfied **do**
  Sort the population individuals in ascending order according to the fitness values
  Calculate the number of dimensions D_{jp} and D_{sp} of junior and senior phases using Eqs. (6) and (7), respectively
  for $i = 1$ to N **do**
    for $d = 1$ to D **do**
      if rand(0,1) < k_r **then**
        /* Junior gaining sharing knowledge phase */
        if rand(0,1) < D_{jp}/D **do**
          Generate $\boldsymbol{x}_{\text{new},i,d}$ using Eq. (4)
        else
        /* Senior gaining sharing knowledge phase */
          Generate $\boldsymbol{x}_{\text{new},i,d}$ using Eq. (5)
        end if
      else
        $\boldsymbol{x}_{\text{new},i,d} = \boldsymbol{x}_{i,d}$
      end if
    end for
  end for
  Evaluate the fitness for each trial vector
  Accept the trial vector if it is better than the target individual
  $t = t + 1$
End while

3.2 Proposed IBGSK

In the original GSK, as described above, the population is encoded by real numbers, and the algorithm uses real arithmetic operations for optimization problems in continuous search space. Therefore, it cannot be applied in discrete search space directly. When applied to solve optimization problems with the discrete binary or integer variables, we need to adopt a transcoding technique to convert individuals from one encoding to another, which is not convenient and efficient. This paper presents an improved binary variant of GSK called IBGSK for the FSL problem of distribution networks. In IBGSK, individuals are represented as binary vectors instead of real vectors. For ease of individual updating, improved junior gaining and sharing phase and improved senior gaining and sharing phase are designed. Furthermore, to increase the population diversity, a binary mutation operator is developed and integrated into IBGSK to avoid premature convergence.

3.2.1 Improved junior gaining and sharing phase

In IBGSK, an improved way is proposed to engender $\boldsymbol{x}_{\mathrm{new},i}^{t}$ for $\boldsymbol{x}_{i}^{t}$:

$$x_{\mathrm{new},i,d}^{t} = x_{i,d}^{t} + k_{f,i,d} \cdot (|x_{i-1,d}^{t} - x_{i+1,d}^{t}| \oplus |x_{r,d}^{t} - x_{i,d}^{t}|) \quad (8)$$

where $\oplus$ stands for the logical exclusive OR (XOR) operator. $|\cdot|$ stands for the absolute value operator.

In the original GSK, the knowledge factor k_f is a constant real number bigger than 0. However, in the proposed IBGSK, k_f is a binary number determined by the following method:

$$k_{f,i,d} = (-1)^{x_{i,d}^{t}} \quad (9)$$

By this, for an individual, different dimensions may have various knowledge factors, increasing the moving diversity. In addition, it makes sure that the value $x_{\mathrm{new},i,d}^{t}$ can only be 0 or 1.

3.2.2 Improved senior gaining and sharing phase

Similarly, an improved way is also proposed to generate $\boldsymbol{x}_{\mathrm{new},i}^{t}$ for $\boldsymbol{x}_{i}^{t}$ in this phase:

$$x_{\mathrm{new},i,d}^{t} = x_{i,d}^{t} + k_{f,i,d} \cdot (|x_{p-\mathrm{best},d}^{t} - x_{p-\mathrm{worst},d}^{t}| \oplus |x_{m,d}^{t} - x_{i,d}^{t}|) \quad (10)$$

where the knowledge factor $k_{f,i,d}$ is also calculated by the method as shown in Eq. (9).

3.2.3 Binary mutation operator

GSK possesses acceptable local search ability while its global search ability is poor. The use of mutation is an effective way to maintain the population diversity and thus to enhance the global search ability [45]. In this paper, a binary mutation operator, as shown below, is integrated into IBGSK to enrich the population diversity.

$$x_{\mathrm{new},i,d}^{t} = 1 - x_{\mathrm{new},i,d}^{t} \quad (11)$$

It is worth noting from Eq. (11) that after those mentioned above two improved phases update an individual, it will be further edited by the binary mutation operator. The possibility that a dimension of an individual undergoes the mutation depends on a mutation probability p_m . The binary mutation operator is presented in **Algorithm 2**.

Algorithm 2: Binary mutation operator

for i = 1 to N **do**
    for d = 1 to D **do**
        if rand(0,1) < p_m **then**
            Generate $\boldsymbol{x}_{\mathrm{new},i,d}$ using Eq. (11)
        end if
    end for
end for

Combining the above three improvements in the original GSK, the proposed IBGSK is obtained and presented in **Algorithm 3**. Compared with the original GSK, the main difference in IBGSK is the mutation operator. The computational complexity of GSK is $O(N \cdot D \cdot t_{\max})$, where $t_{\max}$ is the maximal number of iterations. Since the computational complexity of the mutation operator in each iteration is $O(N \cdot D)$, so the entire computational complexity of IBGSK is $O(2 \cdot N \cdot D \cdot t_{\max})$. Hence, the computational complexity of the proposed IBGSK and GSK are almost the same.

Algorithm 3: The main procedure of IBGSK

Generate a random initial population ***Pop*** in binary search space
Evaluate the fitness for each individual
Initialize the iteration counter t = 1
While the stopping condition is not satisfied **do**
    Sort the population individuals in ascending order according to the fitness values
    Calculate the number of dimensions D_{jp} and D_{sp} of junior and senior phases using Eqs. (6) and (7), respectively
    for i = 1 to N **do**
        for d = 1 to D **do**
            if rand(0,1) < k_r **then**
                /* Improved junior gaining sharing knowledge phase */
                if rand(0,1) < D_{jp}/D **do**
                    Generate $\boldsymbol{x}_{\mathrm{new},i,d}$ using Eq. (8)
                else
                /* Improved senior gaining sharing knowledge phase */
                    Generate $\boldsymbol{x}_{\mathrm{new},i,d}$ using Eq. (10)
                end if
            else
                $\boldsymbol{x}_{\mathrm{new},i,d} = \boldsymbol{x}_{i,d}$
            end if
        end for
    end for

/* Binary mutation operator */
Perform **Algorithm 2**
Evaluate the fitness for each trial vector
Accept the trial vector if it is better than the target individual
$t = t + 1$
End while

3.3 Applying IBGSK for the FSL problem

The framework of applying IBGSK for the FSL problem of distribution networks is shown in Figure 1. The specific steps are shown below:

Step 1: After a fault event occurs, we use both the static and real-time data, including the network topology, FTU configuration, and overcurrent alarms, to construct the objective function.

Step 2: Initialize a random population with N individuals in a discrete search space using the random integer generator function randi(N, D) in MATLAB.

Step 3: Evaluate the objective function value for each individual.

Step 4: Execute the loop program of IBGSK as shown in **Algorithm 3** to update individuals until termination.

Step 5: Stop the calculation and output the best individual, i.e., the final solution.

4. Simulation results and comparisons

4.1 Simulation settings

The following advanced algorithms are implemented and compared to verify the efficiency of the proposed IBGSK in solving the FSL problem of distribution networks.

(1) Binary artificial bee colony algorithm (BABC) [46].

(2) Binary bat algorithm (BBA) [47].

(3) Binary biogeography based optimization (BBBO) [48].

(4) Binary dragonfly algorithm (BDA) [49].

(5) Binary differential evolution (BDE) [50].

(6) Binary particle swarm optimization (BPSO) [22].

(7) Modified binary particle swarm optimization (BPSO) [51].

(8) Binary teaching-learning-based optimization algorithm (BTLBO) [52].

(9) Binary whale optimization algorithm (bWOA) [53].

(10) Binary Jaya algorithm (JayaX) [54].

(11) Oppositional brain storm optimization (OBSO) [43].

(12) Binary GSK optimization algorithm (BGSK) [55].

(13) The original GSK.

For the original GSK, the sigmoid function [53] is used to transform the real vectors into binary vectors when calculating the objective function values. The level division parameter p, knowledge rate, and knowledge ratio for the original GSK and the proposed IBGSK are set to 0.3, 10, and 0.9, respectively. The mutation probability p_m of

IBGSK is set to 0.01. Other algorithms use the same values of parameters in the original literature. In addition, the population size is set to 20 for all algorithms. The maximum number of function evaluations (FEs) used as the termination criteria is set to 5000 for the first test system and 12000 for the second test system. All algorithms are executed 100 independent trials under MATLAB 2017b.

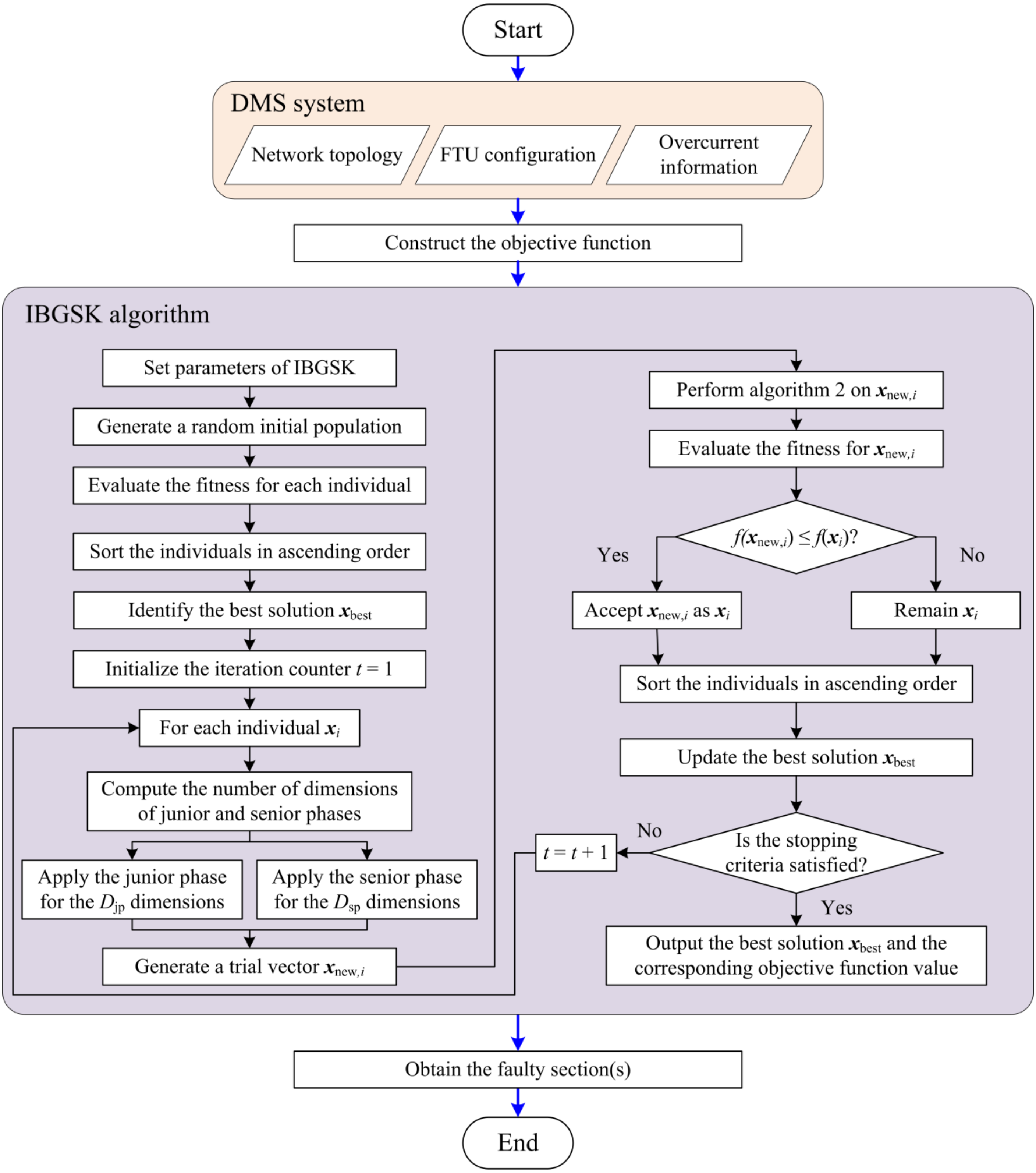

Figure 1 Framework of applying IBGSK to the FSL problem

4.2 IEEE 33-bus distribution network

As shown in Figure 2, this system contains 33 sections and 33 FTUs. Different fault scenarios, as presented in Table 1, are considered.

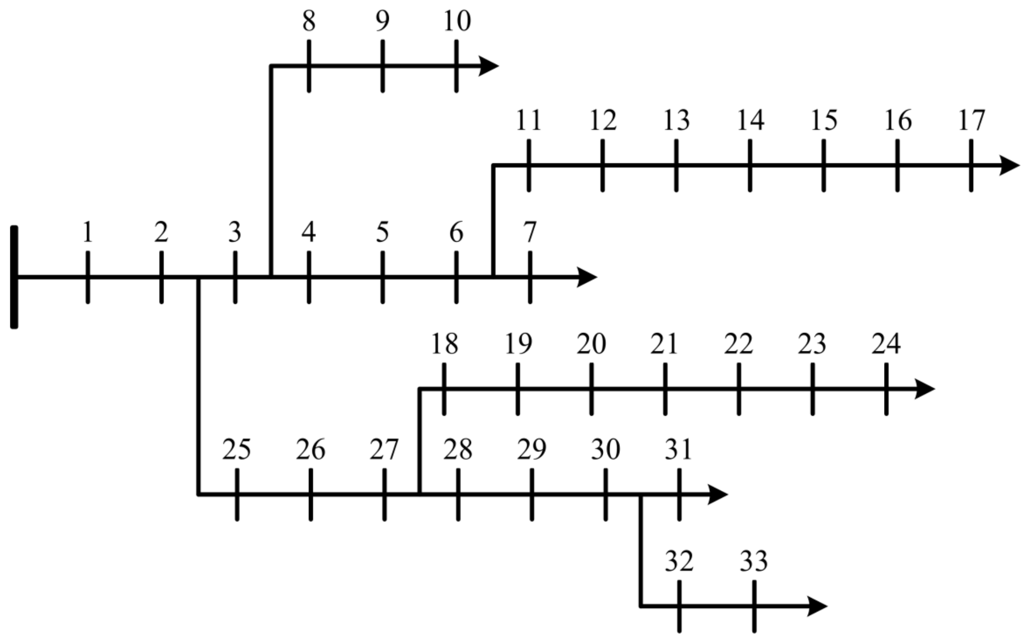

Figure 2 IEEE 33-bus distribution network

Table 1 Typical fault scenarios of the IEEE 33-bus distribution network

Scenario	Overcurrent monitoring points	Wrong signals	Faulty sections
1	1, 2, 3, 4, 5	None	$s_{5\text{-}6}$
2	1, 2, 3, 4, 5, 13	13 (distorted)	$s_{5\text{-}6}$
3	1, 3, 4, 5	2 (lost)	$s_{5\text{-}6}$
4	1, 2, 3, 4, 5, 25, 26, 27	None	$s_{5\text{-}6}$, $s_{27\text{-}18\text{-}28}$
5	1, 2, 3, 4, 5, 13, 25, 26, 27	13 (distorted)	$s_{5\text{-}6}$, $s_{27\text{-}18\text{-}28}$
6	1, 3, 4, 5, 13, 25, 26, 27	2 (lost), 13 (distorted)	$s_{5\text{-}6}$, $s_{27\text{-}18\text{-}28}$

4.2.1 Simulation results

(1) Solution quality

The recorded objective function values of the mean and standard deviation values of 100 independent trials are tabulated in Table 2 and. The least values are highlighted in **boldface**. IBGSK can achieve the best results on all six fault scenarios. Although BDE can also yield the same best results on the first four fault scenarios, its values on the last two fault scenarios are 2.61E+00±1.00E-01 and 3.61E+00±1.00E-01, respectively, which are slightly larger than that of IBGSK. Other algorithms cannot win on even a single fault scenario. In addition, IBGSK is significantly better than the original GSK consistently, indicating that the improved strategies for IBGSK can enhance the performance of GSK distinctly. The above comparison reveals that IBGSK has a better searching ability to achieve high-quality solutions and shows high potential in solving the FSL problem of distribution networks.

Table 2 Objective function values (mean ± standard deviation)

Algorithm	Scenario					
	1	2	3	4	5	6
BABC	3.44E+00±2.44E+00	4.02E+00±1.87E+00	4.45E+00±2.64E+00	4.09E+00±1.29E+00	5.02E+00±1.32E+00	6.15E+00±1.34E+00
BBA	6.27E+00±2.45E+00	7.19E+00±2.45E+00	8.10E+00±2.62E+00	5.42E+00±2.00E+00	6.54E+00±1.52E+00	7.57E+00±1.71E+00
BBBO	8.50E-01±2.19E-01	2.01E+00±5.35E-01	1.91E+00±3.14E-01	1.76E+00±3.68E-01	2.80E+00±4.71E-01	3.78E+00±4.35E-01
BDA	1.52E+00±9.77E-01	2.74E+00±1.08E+00	2.51E+00±1.29E+00	2.44E+00±9.68E-01	3.52E+00±9.33E-01	4.68E+00±1.07E+00
BDE	**8.00E-01±0.00E+00**	**1.80E+00±0.00E+00**	**1.80E+00±0.00E+00**	**1.60E+00±0.00E+00**	2.61E+00±1.00E-01	3.61E+00±1.00E-01
BPSO	8.70E-01±2.93E-01	1.86E+00±2.78E-01	1.82E+00±1.41E-01	1.70E+00±3.02E-01	2.72E+00±3.56E-01	3.67E+00±2.93E-01
MBPSO	8.70E-01±2.56E-01	1.89E+00±3.21E-01	1.88E+00±2.73E-01	1.74E+00±3.49E-01	2.81E+00±4.33E-01	3.76E+00±3.68E-01
BTLBO	5.99E+00±3.30E+00	5.79E+00±2.63E+00	6.24E+00±3.54E+00	5.54E+00±1.60E+00	6.61E+00±1.94E+00	7.43E+00±1.63E+00
bWOA	8.26E-01±1.49E-01	1.81E+00±8.00E-02	1.82E+00±1.37E-01	1.95E+00±5.80E-01	2.94E+00±4.80E-01	4.01E+00±6.10E-01
JayaX	8.08E-01±8.00E-02	1.81E+00±1.00E-01	1.81E+00±1.00E-01	1.61E+00±1.00E-01	2.62E+00±1.41E-01	3.61E+00±1.00E-01
OBSO	7.78E+00±3.52E+00	8.66E+00±3.10E+00	9.40E+00±3.49E+00	6.51E+00±2.89E+00	7.61E+00±2.33E+00	8.02E+00±1.98E+00
GSK	1.52E+00±1.18E+00	2.59E+00±1.15E+00	2.32E+00±8.74E-01	2.26E+00±7.42E-01	3.38E+00±9.65E-01	4.25E+00±7.31E-01
BGSK	1.31E+00±6.35E-01	2.36E+00±6.77E-01	2.31E+00±8.50E-01	2.40E+00±8.38E-01	3.44E+00±7.88E-01	4.35E+00±7.54E-01
IBGSK	**8.00E-01±0.00E+00**	**1.80E+00±0.00E+00**	**1.80E+00±0.00E+00**	**1.60E+00±0.00E+00**	**2.60E+00±0.00E+00**	**3.60E+00±0.00E+00**

(2) Robustness

Robustness is a crucial indicator to evaluate a metaheuristic algorithm's searching stability and consistency. The standard deviation values of 100 independent trials in Table 2 show that IBGSK provides a zero value on all six fault scenarios, indicating that it can consistently achieve the same global best solution in all 100 independent trials. However, other algorithms obtain unstable values on different fault scenarios. Namely, they get different solutions in 100 independent trials. To verify this inference, an index success rate (SR) that is defined to count the number of obtaining the correct solution successfully in 100 independent trials is introduced to analyze the simulation results. Table 3 shows that both IBGSK and BDE can correctly locate the faulty section(s) of the first four fault scenarios. However, BDE fails in one trial on the last two fault scenarios.

Additionally, the SR values of other algorithms are worse and not larger than 99%. For example, the success rate of the original GSK is around 50%, far below that of IBGSK, which indicates that GSK is very unstable and only provides about half the solutions right because it is easy to fall into local optima. In short, IBGSK can locate the global minimum consistently to achieve a reliable and accurate solution for the concerned problem.

Table 3 Success rate (%)

Algorithm	Scenario					
	1	2	3	4	5	6
BABC	17	17	22	1	5	2
BBA	1	2	1	2	1	4
BBBO	95	84	89	84	82	84
BDA	50	46	66	44	39	33
BDE	**100**	**100**	**100**	**100**	99	99
BPSO	94	95	98	90	89	94
MBPSO	93	92	92	86	80	84
BTLBO	6	6	10	1	10	1
bWOA	97	99	97	70	65	65
JayaX	99	99	99	99	98	99
OBSO	3	3	2	1	2	4
GSK	54	52	56	47	48	47
BGSK	56	53	63	44	38	42
IBGSK	**100**	**100**	**100**	**100**	**100**	**100**

Finally, Figure 3 plots the convergence curves against the mean objective function values. As can be seen, bWOA converges the fastest in the early stage. However, it runs into the problem of stagnation quickly, especially on the last three fault scenarios. Although IBGSK converges slowly in the first half stage, it is very fast in the middle period of the evolution and surpasses all other algorithms. Besides, compared with the original GSK, the proposed IBGSK is slower in the first half stage but quicker in the second half stage, indicating that the original GSK has fallen into local optima while IBGSK can get rid of local optima to locate more promising areas.

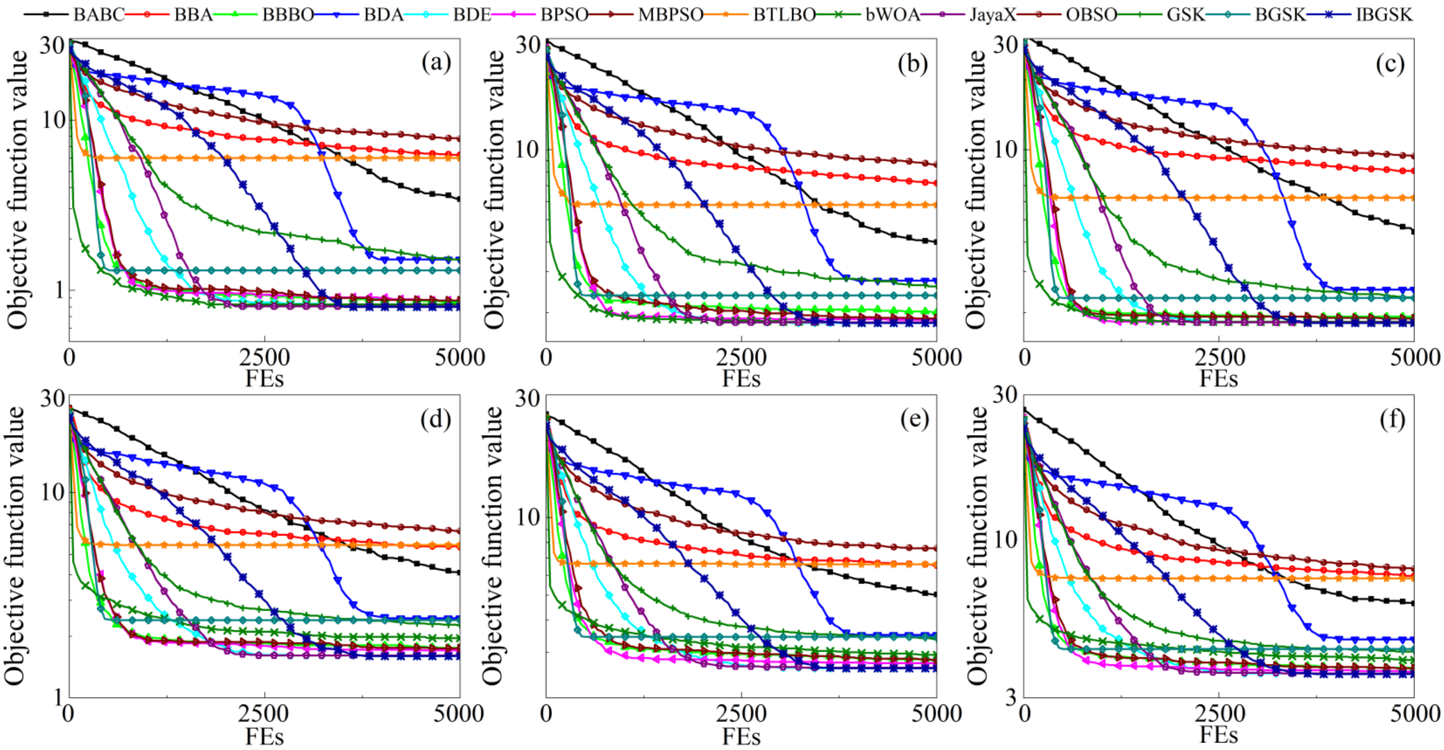

Figure 3 Convergence curves for the IEEE 33-bus distribution network. (a) Fault scenario 1. (b) Fault scenario 2. (c) Fault scenario 3. (d) Fault scenario 4. (e) Fault scenario 5. (f) Fault scenario 6

(4) Statistical analysis

This section compares the algorithms statistically based on the multiple-problem Friedman test at a confidence level of 5% to highlight the advantage of the proposed IBGSK. This test takes all the six fault scenarios together to rank the algorithms according to the success rate values, as shown in Figure 4. IBGSK performs the overall best, consistent with the conclusion obtained by the results in Table 2. BDE gets a second place as it can achieve the correct solutions in all 100 independent trials for the first four fault scenarios, followed by JayaX, BPSO, bWOA, MBPSO, BBBO, GSK, BGSK, BDA, BABC, BTLBO, OBSO, and BBA. The test result presents that the proposed IBGSK is significantly better than the original GSK and proves its advanced effectiveness for the FSL problem of distribution networks.

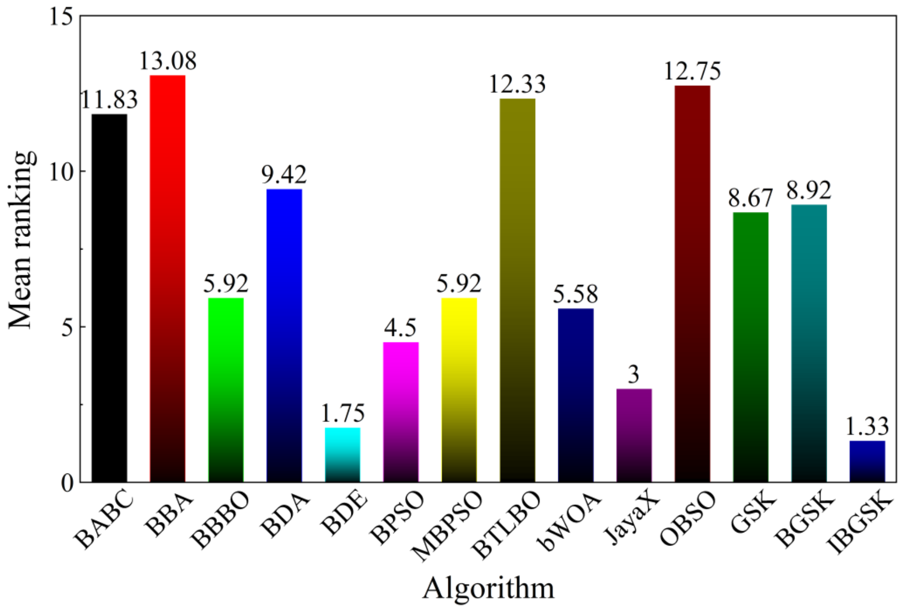

Figure 4 Friedman test result

4.2.2 Effect of mutation probability

In the proposed IBGSK, a binary mutation operator is integrated to enhance the population diversity. This subsection investigates the effect of mutation probability pm on IBGSK. Different values are set for p_m, as shown in Table 4. The mutation probability does affect the performance of IBGSK when it is within a specific range, while too large or too small mutation probability is not beneficial for IBGSK. The primary cause for such effect is that p_m controls the equilibrium between exploitation and exploration. Although a large p_m favors helping individuals escape from local optima to enhance the global search, the possibility of changing individuals' positions is so frequent that it slows down the convergence rate. On the other hand, a small p_m can reduce the likelihood of changing individuals' positions to accelerate the convergence. However, the population diversity is also decreased, and individuals are likely to be caught in local optima.

Table 4 Effect of mutation probability on IBGSK (objective function value (mean ± standard deviation) and success rate (%))

p_m	Scenario					
	1	2	3	4	5	6
0	9.16E-01±7.99E-01 95	1.86E+00±2.19E-01 95	1.86E+00±2.39E-01 94	1.68E+00±2.73E-01 92	2.69E+00±2.88E-01 91	3.69E+00±2.82E-01 91
0.001	8.40E-01±1.97E-01 96	1.85E+00±2.61E-01 96	1.83E+00±1.61E-01 97	1.64E+00±1.88E-01 96	2.65E+00±2.19E-01 95	3.64E+00±1.97E-01 96
0.005	**8.00E-01±0.00E+00** **100**	**1.80E+00±0.00E+00** **100**	**1.80E+00±0.00E+00** **100**	1.61E+00±8.00E-02 99	2.61E+00±1.00E-01 99	3.61E+00±1.00E-01 99
0.01	**8.00E-01±0.00E+00** **100**	**1.80E+00±0.00E+00** **100**	**1.80E+00±0.00E+00** **100**	**1.60E+00±0.00E+00** **100**	**2.60E+00±0.00E+00** **100**	**3.60E+00±0.00E+00** **100**

0.02	**8.00E-01±0.00E+00**	**1.80E+00±0.00E+00**	**1.80E+00±0.00E+00**	1.61E+00±8.00E-02	**2.60E+00±0.00E+00**	3.61E+00±1.00E-01
	100	**100**	**100**	99	**100**	99
0.05	1.56E+00±1.01E+00	2.40E+00±7.30E-01	2.32E+00±6.41E-01	2.29E+00±6.48E-01	3.25E+00±6.78E-01	4.41E+00±6.67E-01
	48	47	51	34	40	29
0.1	6.04E+00±2.02E+00	6.71E+00±1.81E+00	7.50E+00±2.03E+00	5.24E+00±1.22E+00	6.12E+00±1.33E+00	7.10E+00±1.11E+00
	0	0	0	0	1	0

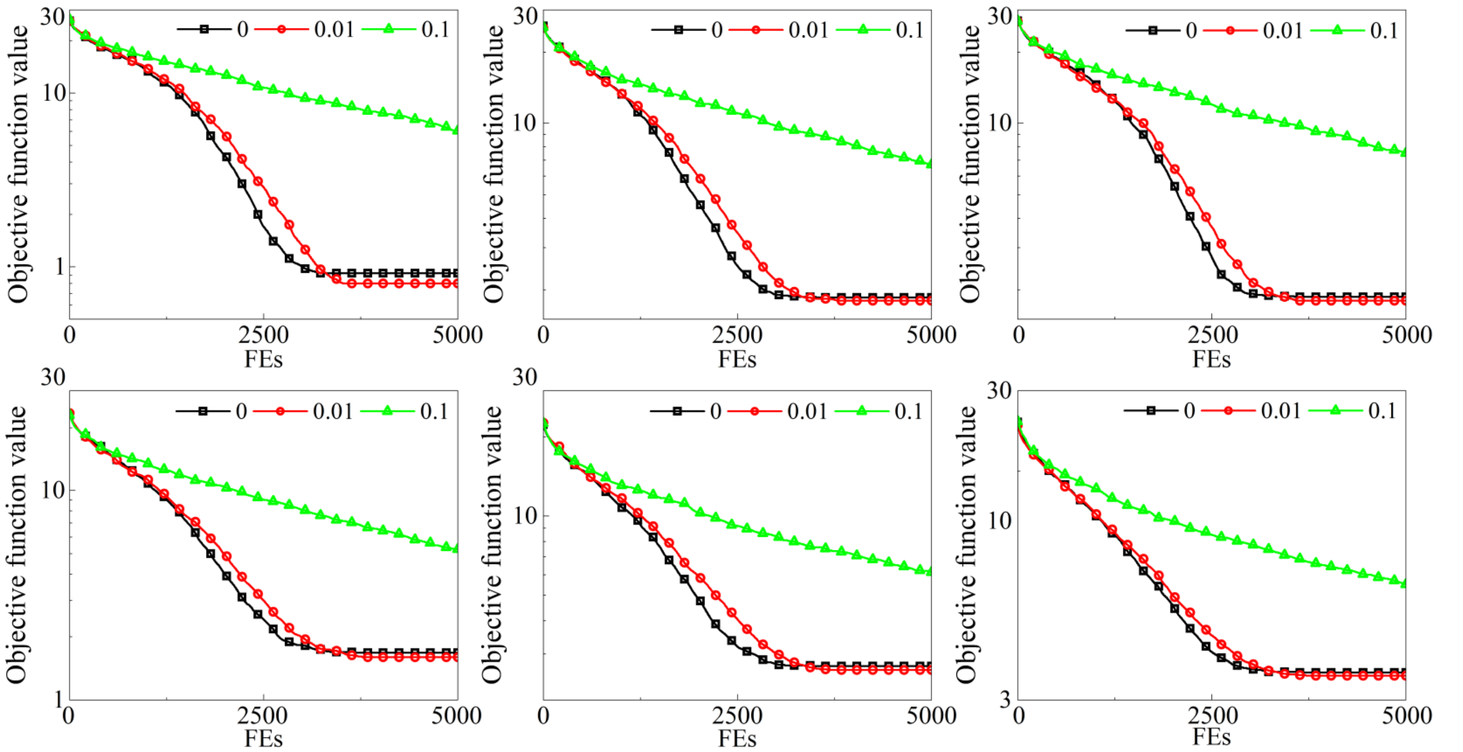

Figure 5 Convergence curves to show the effect of mutation probability on IBGSK. (a) Fault scenario 1. (b) Fault scenario 2. (c) Fault scenario 3. (d) Fault scenario 4. (e) Fault scenario 5. (f) Fault scenario 6

The graph against different mutation probabilities, as shown in Figure 5, also supports the above deduction. In addition, the results in Table 4 and Figure 5 also indicate that the lack of the binary mutation operator will worsen the performance of IBGSK. In summary, the binary mutation operator is essential to enhance the effectiveness of IBGSK, and a mutation probability of proper value, neither too large nor too small, is conducive to IBGSK.

4.3 USA PG&E 69-bus distribution network

In this test system, a more complicated fault scenario is considered, as shown in Figure 6. As tabulated in Table 5, this fault scenario contains four faulty sections, three distorted signals, and three lost signals. The simulation results presented in Table 6 indicate that this fault scenario is so complicated that all algorithms drop their performance in varying degrees compared with the first test system. Even so, the proposed IBGSK still shows its strong robustness. It misses only one trial in 100 independent trials and outperforms other competing algorithms consistently in terms of objective function value and success rate. As a consequence, it achieves the first ranking legitimately. The convergence graph in Figure 7 shows that although IBGSK is relatively slow in the initial stage, it keeps up fast throughout the evolution process and finally exceeds other algorithms. The original GSK is faster than IBGSK in the first half stage but quickly stagnates, indicating it has been trapped in a local optimum. This fault scenario demonstrates again that IBGSK has a powerful ability to jump out of local optima and achieve a high-quality solution for the FSL problem of distribution networks.

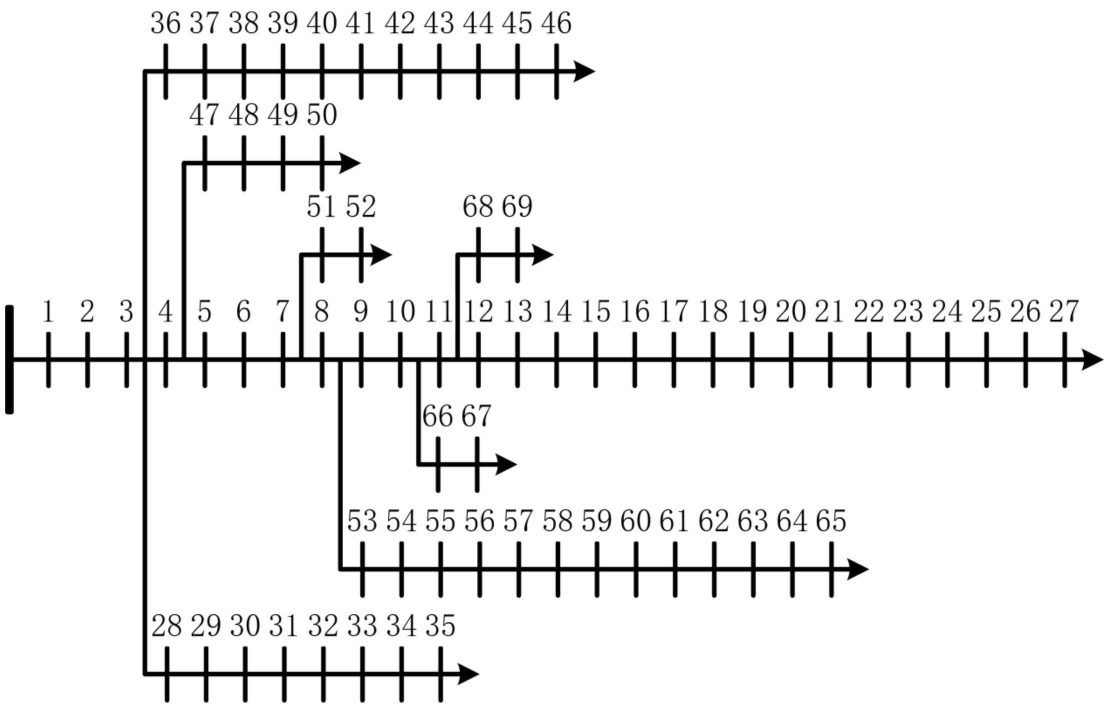

Figure 6 USA PG&E 69-bus distribution network

Table 5 Fault scenario of the USA PG&E 69-bus distribution network

Overcurrent monitoring points	Distorted signals	Lost signals	Faulty sections
1, 2, 3, 4, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 37, 38, 39, 40, 53, 54, 55, 68, 69	24, 26, 31	5, 6, 36	$s_{18\text{-}19}$, $s_{40\text{-}41}$, $s_{55\text{-}56}$, s_{69}

Table 6 Simulation results of the USA PG&E 69-bus distribution network

Algorithm	Objective function value (mean ± standard deviation)	Success rate (%)	Ranking[a]
BABC	1.77E+01±3.17E+00	0	11
BBA	2.95E+01±3.53E+00	0	14
BBBO	9.31E+00±3.09E-01	89	3
BDA	1.41E+01±2.50E+00	3	8
BDE	9.34E+00±3.07E-01	83	5
BPSO	9.37E+00±4.03E-01	84	4
MBPSO	9.41E+00±4.09E-01	79	6
BTLBO	2.11E+01±3.94E+00	0	12
bWOA	1.20E+01±1.07E+00	1	9
JayaX	9.28E+00±2.69E-01	92	2
OBSO	2.64E+01±4.55E+00	0	13
GSK	1.32E+01±1.93E+00	1	10
BGSK	1.10E+01±1.29E+00	16	7
IBGSK	**9.21E+00±1.00E-01**	**99**	**1**

[a] The ranking result is first yielded based on the success rate value. If two algorithms have the same success rate, the one that has the less objective function value achieves a better ranking.

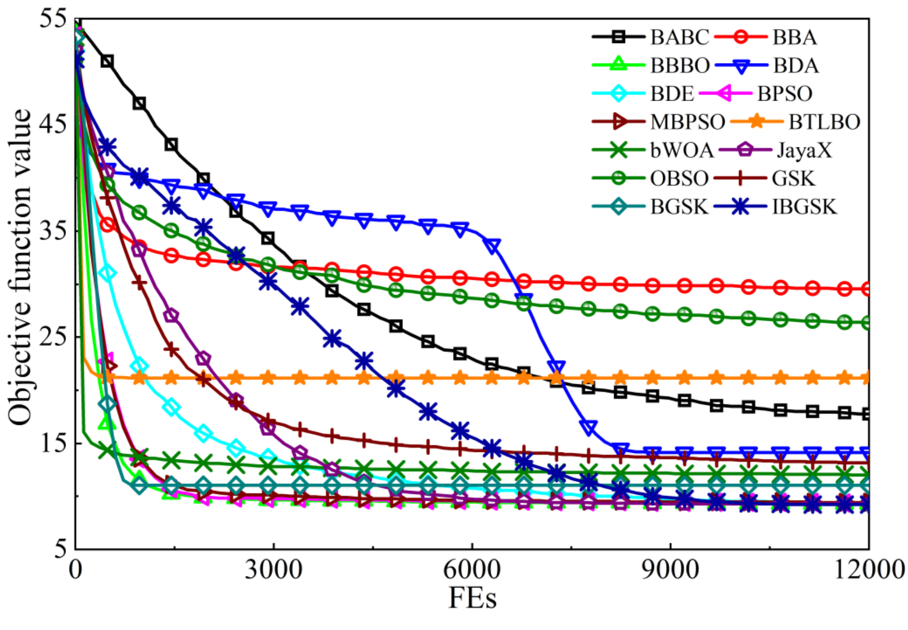

Figure 7 Convergence curves for the USA PG&E 69-bus distribution network

4.4 Discussions

From the above simulation results and comparisons, the following important insights can be summarized:

(1) IBGSK demonstrates remarkably competing achievements in terms of solution quality, robustness, and convergence property. It can diagnose different fault

scenarios with 100% and 99% success rates for these two test systems, yield the first ranking among all benchmarking algorithms.

(2) The binary mutation operator is an indispensable part of IBGSK. Too large the mutation probability can maintain the population diversity but will slow down the convergence rate. On the other hand, although a too-small value can promote premature convergence, it will easily catch the algorithm in local optima. Therefore, a modest mutation probability p_{m} with a value of 0.01 is highly suggested to adequately harmonize the exploitation and exploration in solving the FSL problem.

(3) Although the original GSK is faster than IBGSK in the first half stage, it quickly encounters the problem of premature convergence in the second half stage, resulting in low-quality solutions. IBGSK has a preeminent convergence rate, especially in the middle and later stages, indicating that it can successfully get rid of local optima to achieve high-quality solutions.

(4) Compared with the IEEE 33-bus distribution network, the USA PG&E 69-bus distribution network has a larger scale and more distribution sections, meaning more decision variables. As a result, the involved algorithms fail in more trials, including the proposed IBGSK, which fails in one trial. This result illustrates that IBGSK is not always omnipotent in dealing with more complex test systems and fault scenarios.

5. Conclusions and future works

An improved binary GSK referred to as IBGSK is proposed to identify the faulty section(s) of distribution networks. In IBGSK, individuals are encoded as binary vectors rather than real vectors. The junior gaining and sharing phase and senior gaining and sharing phase are improved with individuals being updated directly in binary search space. Meanwhile, a binary mutation operator is integrated into IBGSK to balance the exploitation and exploration. Extensive simulation and comparison, based on fault scenarios of the IEEE 33-bus distribution network and USA PG&E 69-bus distribution network, are conducted to demonstrate the excellent efficiency of IBGSK. Compared with other algorithms, IBGSK shows superior performance with more efficient convergence in avoiding the problems of trapping into local optima. It achieves smaller objective function values and higher success rates, further validated by the Friedman test.

Several future work directions are planned to enhance the proposed IBGSK further. Firstly, adaptive mutation probability will be investigated, where the mutation probability can be changed throughout the evolution process to adapt to different distribution networks and fault scenarios. Secondly, some local search operators or algorithms can be hybridized to boost the convergence further, especially during the initial stage. Lastly, the performance of IBGSK can be further verified in more complex distribution networks and practical systems.

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References

[1] M. Kezunovic, Smart Fault Location for Smart Grids, IEEE Trans. Smart Grid 2 (2011) 11-22.

[2] C. Orozco-Henao, A.S. Bretas, R. Chouhy-Leborgne, A.R. Herrera-Orozco, J. Marín-Quintero, Active distribution network fault location methodology: A minimum fault reactance and Fibonacci search approach, Int. J. Elec. Power 84 (2017) 232-241.

[3] S.S. Gururajapathy, H. Mokhlis, H.A. Illias, Fault location and detection techniques in power distribution systems with distributed generation: A review, Renew. Sust. Energy Rev. 74 (2017) 949-958.

[4] M. Shafiullah, M.A. Abido, A review on distribution grid fault location techniques, Electr. Pow. Compo. Sys. 45 (2017) 807-824.

[5] V. Calderaro, V. Galdi, A. Piccolo, P. Siano, A Petri net based protection monitoring system for distribution networks with distributed generation, Electr. Pow. Syst. Res. 79 (2009) 1300-1307.

[6] C. Yuan, Y. Liao, L. Kong, H. Xiao, Fault diagnosis method of distribution network based on time sequence hierarchical fuzzy petri nets, Electr. Pow. Syst. Res. 191 (2021) 106870.

[7] I. Kiaei, S. Lotfifard, Fault section identification in smart distribution systems using multi-source data based on fuzzy Petri nets, IEEE Trans. Smart Grid 11 (2019) 74-83.

[8] C. Zheng, G. Zhu, F. Qin, J. Lan, S. Li. Distribution network fault segment location algorithm based on Bayesian estimation in intelligent distributed control mode, in Proceedings of the 2020 Asia Energy and Electrical Engineering Symposium (AEEES), IEEE, pp 592-596.

[9] Z. Sun, Q. Wang, Z. Wei, Fault location of distribution network with distributed generations using electrical synaptic transmission-based spiking neural P systems, Int. J. Parall. Emerg. Distr. Sys. 36 (2021) 11-27.

[10] T. Zhang, L. Sun, J. Liu, H. Yu, X. Zhou, L. Gao, Y. Zhang, Fault diagnosis and location method for active distribution network based on artificial neural network, Electr. Pow. Compo. Sys. 46 (2018) 987-998.

[11] S. Hou, W. Guo. Fault identification method for distribution network based on parameter optimized variational mode decomposition and convolutional neural network. IET Gener. Transm. Dis. (2021) 1-13.

[12] Y. Yu, M. Li, T. Ji, Q. H. Wu. Fault location in distribution system using convolutional neural network based on domain transformation, CSEE J. Power Energy 7(3) (2021) 472-484.
[13] H. Yan, X. Wu, C. Lin, H. Liu. A Modified Matrix Algorithm Dichotomy for Distribution Network Fault Location, in Proceedings of the 2020 International Conference of Recent Trends in Environmental Sustainability and Green Technologies (ICRTEG 2020), pp 2010.
[14] M. Dashtdar, M. Dashtdar. Fault location in the distribution network based on scattered measurement in the network, Energy Syst. (2021) 1-24.
[15] W. Deng, J. Xu, X. Z. Gao, H, Zhao. An enhanced MSIQDE algorithm with novel multiple strategies for global optimization problems, IEEE Trans. Syst. Man. CY. Syst. (2020) in press.
[16] W. Deng, S. Shang, X. Cai, H. Zhao, Y. Zhou, H. Chen, W Deng. Quantum differential evolution with cooperative coevolution framework and hybrid mutation strategy for large scale optimization, Knowl-Based Sys. 224 (2021) 107080.
[17] G. Xiong, J. Zhang, D. Shi, L. Zhu, X. Yuan, Parameter extraction of solar photovoltaic models via quadratic interpolation learning differential evolution, Sustain. Energ. Fuels 4 (2020) 5595-5608.
[18] G. Xiong, J. Zhang, D. Shi, L. Zhu, X. Yuan, Parameter extraction of solar photovoltaic models with an either-or teaching learning based algorithm, Energ. Convers. Manage. 224 (2020) 113395.
[19] X. Wang, X. Yu, Y. Xue, Y. Zhu, J. Fu. Application of Improved Quantum Genetic Algorithm in Fault Location of Distribution Network, in Proceedings of the 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC 2018), IEEE, pp 2524-2529.
[20] M. Gong, Z. Xu, Y. Xie, J. Pan, R. Li. Fault-section location of distribution network containing distributed generation based on the multiple-population genetic algorithm of chaotic optimization, in Proceedings of the 2017 Chinese Automation Congress (CAC), IEEE, pp 4984-4988.
[21] H. R. Li, Research on fault location of power distribution network based on fault data information, Telecommunications and Radio Engineering 79(8) (2020) 713-722.
[22] L. Cao, J. He, K. Li, S. Zhou, F. Yang. Research on distribution network fault location based on binary particle swarm optimization, in Proceedings of the AIP Conference Proceedings, AIP Publishing LLC, 2154 (2019), pp 20032.
[23] K. C. Chang, R. S. Zhang, H. Q. Deng, F. H. Chang, H. C. Wang, Chaotic Particle Swarm Optimization Algorithm for Fault Location of Distribution Network with DG, in Proceedings of the International Conference on Advanced Intelligent Systems and Informatics (AISI) (2021) pp 256-266.

[24] M. Zhao, Y. Zhang, Fault section location for distribution network containing DG based on IBQPSO, J. Comput. Method Sci. Eng. 20 (2020) 937-949.

[25] Q. Wang, T. Jin, M.A. Mohamed, An innovative minimum hitting set algorithm for model-based fault diagnosis in power distribution network, IEEE Access 7 (2019) 30683-30692.

[26] H. SHI, Q. TAN, C. LI. Fault section location for distribution network with DG based on binary hybrid algorithm, in Proceedings of International Conference on Mechanical and Mechatronics Engineering (ICMME), IEEE (2017), pp 109-114.

[27] H. Yang, Y. Guo, X. Liu, Fault Section Location of Active Distribution Network based on Wolf Pack and Differential Evolution Algorithms, Int. J. Performability Engineering 16(1) (2020) 143-151.

[28] X. Huang, Z. Xie, X. Huang, Fault location of distribution network base on improved cuckoo search algorithm, IEEE Access 8 (2019) 2272-2283.

[29] Z. Li, X. Zhang, Q. Song, N. Wu. Fault Location of Active Distribution Network Based on Improved Gray Wolf Algorithm, in Proceedings of the 2020 Chinese Automation Congress (CAC), IEEE, pp 962-967.

[30] Y. Sun, H. Wu, Y. Zhu, Y. Wei, T. Zhao, Fault-Section Location of Distribution Network based on Adaptive Mutation Shuffled Frog Leaping Algorithm, Int. J. Perform. Eng. 15 (2019) 1220.

[31] K. Jiang, X. Tong. Fault section location method based on fuzzy self-correction bat algorithm in non-solidly earthed distribution network, in Proceedings of the 2nd International Conference on Power and Renewable Energy (ICPRE), IEEE, pp. 485-489.

[32] J. Zhou, S. Shi, Y. Cui, Y. Su, M. Wang, C. Wu. Fault Location for Multi-source Distribution Network Based on Improved Chaotic Jaya Algorithm, Journal of Physics: Conference Series, 2095 (2021), 012016.

[33] Y. Li, X. Wei, J. Lin, G. Niu. Fault location method of distribution network based on fruit fly optimization algorithm, in Proceedings of the 16th IET International Conference on AC and DC Power Transmission (ACDC 2020), IET, pp 2160-2165.

[34] W. Deng, J. Xu, H. Zhao, Y. Song. A novel gate resource allocation method using improved PSO-based QEA, IEEE Trans. Intell. Transp. (2020) in press.

[35] W. Deng, S. Shang, X. Cai, H. Zhao, Y. Song, J. Xu. An improved differential evolution algorithm and its application in optimization problem, Soft Comput. 25 (2021) 5277–5298.

[36] W. Deng, J. Xu, Y. Song, H. Zhao. An effective improved co-evolution ant colony optimisation algorithm with multi-strategies and its application, Int. J. Bio-Inspir. Com. 16(3) (2020) 158-170.

[37] X. Liu, J. Jia, J. Wang. Research on IACA of distribution network fault location, Journal of Physics: Conference Series, 1654 (2020) 012106.

[38] G. Xiong, J. Zhang, X. Yuan, D. Shi, Y. He, G. Yao. Parameter extraction of solar photovoltaic models by means of a hybrid differential evolution with whale optimization algorithm, Sol. Energy, 176 (2018) 742-761.
[39] G. Xiong, J. Zhang, D. Shi, L. Zhu, X. Yuan. Optimal identification of solid oxide fuel cell parameters using a competitive hybrid differential evolution and Jaya algorithm. Int. J. Hydrogen Energ. 46(9) (2021) 6720-6733.
[40] A.W. Mohamed, A.A. Hadi, A.K. Mohamed, Gaining-sharing knowledge based algorithm for solving optimization problems: a novel nature-inspired algorithm, Int. J. Mach. Learn. Cyb. 11 (2020) 1501-1529.
[41] G. Xiong, L. Li, A. W. Mohamed, X. Yuan, J. Zhang. A new method for parameter extraction of solar photovoltaic models using gaining–sharing knowledge based algorithm, Energy Rep. 7(2021) 3286-3301.
[42] G. Xiong, X. Yuan, A. W. Mohamed, J. Zhang. Fault section diagnosis of power systems with logical operation binary gaining-sharing knowledge-based algorithm, International Journal of Intelligent Systems, 37 (2022) 1057-1080.
[43] G. Xiong, J. Zhang, D. Shi, Y. He, Oppositional Brain Storm Optimization for Fault Section Location in Distribution Networks, In: Cheng S., Shi Y. (eds) Brain Storm Optimization Algorithms. Adaptation, Learning, and Optimization, vol 23. Springer, Cham., Springer (2019) pp 61-77.
[44] Y. Guo, G. Xiong, Fault section location in distribution network by means of sine cosine algorithm. Power Syst. Prot. Control 45(2017) 97-101.
[45] G. Xiong, J. Zhang, D. Shi, L. Zhu, X. Yuan, Z. Tan. Winner-leading competitive swarm optimizer with dynamic Gaussian mutation for parameter extraction of solar photovoltaic models, Energ. Convers. Manage. 206 (2020) 112450.
[46] Y. He, H. Xie, T. Wong, X. Wang, A novel binary artificial bee colony algorithm for the set-union knapsack problem, Future Gener. Comp. Sy. 78 (2018) 77-86.
[47] S. Mirjalili, S.M. Mirjalili, X. Yang, Binary bat algorithm, Neural Comput. Appl. 25 (2014) 663-681.
[48] X. Li, M. Yin, Multiobjective binary biogeography based optimization for feature selection using gene expression data, IEEE Trans. Nanobiosci. 12 (2013) 343-353.
[49] S. Mirjalili, Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems, Neural Comput. Appl. 27 (2016) 1053-1073.
[50] A. Karbassi Yazdi, M.A. Kaviani, T. Hanne, A. Ramos, A binary differential evolution algorithm for airline revenue management: a case study, Soft Comput. 24 (2020) 14221-14234.

[51] S. Lee, S. Soak, S. Oh, W. Pedrycz, M. Jeon, Modified binary particle swarm optimization, Prog. Nat. Sci. 18 (2008) 1161-1166.

[52] M. Allam, M. Nandhini, Optimal feature selection using binary teaching learning based optimization algorithm, J. King Saud Univ. – Comput. Inform. Sci. (2018) in press.

[53] A.G. Hussien, A.E. Hassanien, E.H. Houssein, S. Bhattacharyya, M. Amin, S-shaped binary whale optimization algorithm for feature selection, In: Bhattacharyya S., Mukherjee A., Bhaumik H., Das S., Yoshida K. (eds) Recent Trends in Signal and Image Processing. Advances in Intelligent Systems and Computing, vol 727 (2019). Singapore, Springer, pp 79-87.

[54] M. Aslan, M. Gunduz, M.S. Kiran, JayaX: Jaya algorithm with xor operator for binary optimization, Appl. Soft Comput. 82 (2019) 105576.

[55] P. Agrawal, T. Ganesh, A.W. Mohamed, A novel binary gaining–sharing knowledge-based optimization algorithm for feature selection, Neural Comput. Appl., 33 (2021) 5989–6008.