Research Article

Design on Universal Circuit Breaker via Improved Gray Wolf Optimization Algorithm

Shuidong Dai, Kewen Xia, Lili Shi, and Min Xie

School of Electronics and Information Engineering, Hebei University of Technology, Tianjin 300401, China

Correspondence should be addressed to Kewen Xia; kwxia@hebut.edu.cn

Received 23 September 2019; Accepted 9 April 2020; Published 27 May 2020

Academic Editor: Nunzio Salerno

Copyright © 2020 Shuidong Dai et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Miniaturization design of the universal circuit breaker is very necessary, but it is not enough to consider only the miniaturization in the design but also consider the energy consumption and breaking capacity of the universal circuit breaker. To this end, a comprehensive optimization design method in this paper is proposed and studied. Firstly, based on the analysis of the universal circuit breaker miniaturization model, combines with the universal circuit breaker’s low energy consumption model and high-segmentation model, a comprehensive optimization model for designing universal circuit breakers is constructed. Secondly, for the comprehensive model solution, an improved gray wolf optimization (GWO) algorithm is proposed, that is, a “cloud model” is introduced to balance the local search and global search capabilities to improve the convergence speed; also, a weight strategy is introduced to avoid falling into the local minimum, and simulations of typical test functions show that the improved algorithm is superior to other algorithms. Finally, the improved gray wolf optimization algorithm is applied to the comprehensive optimization design of universal circuit breakers. The experimental results show that the proposed comprehensive design method is feasible and improves the design accuracy and efficiency of the universal circuit breaker.

1. Introduction

Under the new trend of rapid development of new energy and smart grids, the scale of the power supply and distribution market continues to expand, which requires higher and higher reliability and operation of power grid [1]. As common switchgear, universal circuit breakers are used to connect and disconnect current to protect electrical equipment and distribution lines from overcurrent damage and undervoltage damage due to short circuits [2]. With the increase of daily power consumption, the optimization requirements for universal circuit breakers are very strict to ensure the safe operation of the power grid [3]. Among them, the optimization of universal circuit breakers is mainly reflected in energy saving, high breaking, miniaturization, and communication [4, 5].

In order to solve the problem of the large volume of the universal circuit breaker, the research on the miniaturization of the universal circuit breaker is very necessary. The miniaturization of the universal circuit breaker is mainly to study the contact system of the universal circuit breaker. The contact system is mainly used to break the fault circuit and connect the short-circuit current [6]. When the contact system starts to work, it will generate a large electric repulsive force. That is, it requires a very large contact pressure [7]. This, therefore, makes it difficult to meet the requirements of miniaturization. To meet the design requirements of miniaturization, it is necessary to optimize the design of contact springs and energy storage and improve the arc extinguishing chamber.

If we only study the miniaturization of the universal circuit breaker, there will still be some problems. Therefore, when we study the miniaturization, we should also analyze the energy consumption and breaking capacity of the universal circuit breaker. In terms of low energy consumption of universal circuit breakers, one is to save energy and materials and the other is to protect the environment with low carbon. When the universal circuit breaker is in a normal working state, the loss of electrical energy is related to many factors: the number and resistance of contact
resistances, phase-offset cosine, copper loss, and so on [8]. In the universal circuit breaker high breaking, the requirements of the universal circuit breaker breaking ability is strong, that is, the limit-breaking current of the universal circuit breaker is large. When there is a short circuit in the circuit, the current is too large. At this time, the universal circuit breaker protection circuit is required, otherwise it will cause a fire, the loss of people's life and property, among which the rapid disconnection of the arc between the dynamic and static contacts is the key to improve the breaking capacity. It can be said that the shorter the arc stagnation time after the dynamic and static contacts are separated, the higher the breaking capacity [9]. Therefore, when we design the universal circuit breaker, three factors should be considered: miniaturization, low energy consumption, and high breaking. Comprehensive optimization of the universal circuit breaker will not only solve the problem of large volume and high energy consumption but also make the breaking capacity higher.

In recent years, with the development of electrical characteristic simulation and digital design, the extensive application of the intelligent information processing algorithm has replaced the traditional design methods of experience and trial algorithm design. This has effectively improved the efficiency of engineering design [10–12]. For example, the particle-based Euclidean distance, improved particle swarm optimization (PSO) algorithm [13] for optimal design of permanent magnet synchronous motors, and improved fuzzy performance reliability algorithm in dynamic systems (PPR) had been employed [14].

The APSO algorithm is an improved adaptive particle swarm optimization algorithm [15], which searches for particles following the optimal particles in the solution space and solves the shortcomings of slow convergence speed and easily fall into the local optimum of the basic PSO algorithm. The cultural differential evolution algorithm (CDE) [16] combined the cultural algorithm and the differential evolution algorithm to solve the traditional differential evolution algorithm’s slow convergence rate and easy to fall into the local minimum problem. Artificial bee colony algorithm (ABC) is a heuristic search technology based on swarm intelligence, which can mimic the foraging behavior of bees. Due to its advantages of few control parameters and strong global search ability, it is widely used in many fields, such as training neural networks [17], data clustering [18], business travel problems [19], and engineering optimization [20].

The GWO algorithm [21] is a new algorithm proposed by Mirjalili et al. In 2004, its performance is superior to other algorithms [22]. However, the GWO algorithm has some defects. To solve these problems, Teng et al. [23] combined the PSO algorithm with the GWO algorithm and proposed a hybrid wolf optimization algorithm based on particle swarm optimization (PSO_GWO); they introduced the idea of particle swarm optimization algorithm into the GWO algorithm, and the individual optimal value and the population optimal value were combined to update the position information of the gray wolf individuals in order to retain the optimal position of the gray wolf individuals.

In addition, the “cloud model” was proposed by Liu et al. [24], and it is mainly used to describe the conversion model between qualitative concepts and quantitative representations. This model can improve the convergence speed of optimization algorithms [25]. Using a weighting strategy and linear weighting can balance the relationship between global search ability and local search ability [26, 27].

In summary, if the normal “cloud model” and weighting strategy are introduced into the GWO algorithm, the shortcomings of the basic GWO algorithm can be solved. The improved GWO algorithm is used to comprehensively optimize the design of the universal circuit breaker, which can enhance the performance of the GWO algorithm and improve the design efficiency of the universal circuit breaker. Therefore, studying the comprehensive design of universal circuit breakers based on intelligent optimization algorithms has important theoretical significance and practical value.

2. Universal Circuit Breaker Optimization Model

2.1. Universal Circuit Breaker Miniaturization Optimization Model

2.1.1. Analysis of Universal Circuit Breaker Miniaturization. Under the normal working conditions of the universal circuit breaker, if the mass and volume of the energy storage spring can be minimized, the design goal of miniaturization of the universal circuit breaker can be achieved.

The energy storage spring is located in the operating mechanism of the universal circuit breaker. The structure of the cylindrical coil spring is shown in Figure 1.

The volume of the spring wires is as follows:

\[ V_s = \frac{\pi}{4} n d^2 L, \]

where \( n \) is the spring coil number and \( L \) is the expansion length of the spring wires.

The mass formula of the springs is

\[ M = \frac{\pi}{4} \rho_1 d^2 L, \]

where \( \rho_1 \) is the spring density.

The volume of the springs is

\[ V = \frac{\pi}{4} D^2 H. \]

According to the design requirements of the universal circuit breakers, there are some relationships:

\[ \left\{ \begin{array}{l} L = \pi (n + 2) D, \\ H = 540 \frac{d^4}{D^2} + 1.5 d. \end{array} \right. \]

The design of springs needs to combine the corresponding constraints, including stiffness constraints, strength constraints, and fatigue strength constraints. According to the different external forces and functions of the spring, the spring structure is designed reasonably with the constraint conditions:

(1) The constraint formula of the spring stiffness condition is
Figure 1: Structure of a cylindrical coil spring, where $H$ is the length of the spring, $d$ is the spring wire diameter, $D$ is the spring middle diameter, and $t$ is the pitch of the spring.

\[ \lambda_{\text{max}} = \frac{8PC^2n}{Gd} = \frac{8PD^2n}{Gd^4} \geq \lambda_{\text{min}}, \]  

(5)

where $\lambda_{\text{max}}$ is the maximum deformation of the spring, $\lambda_{\text{min}}$ is the minimum deformation of the spring, $G$ is the shear modulus of the spring wire, and $C$ is the aspect ratio of the spring.

(2) The static strength conditional constraint formula is

\[ \tau_{\text{max}} = \frac{8KP_{\text{max}}D}{nd} \leq \tau, \]  

(6)

where $\tau_{\text{max}}$ is the maximum shear strength, $P_{\text{max}}$ is the maximum working load, and $K$ is the spring curvature coefficient.

The spring curvature coefficient can be obtained by the spring winding ratio:

\[ K = \frac{4C - 1}{4(C - 1)} + \frac{0.615}{C}, \]  

\[ C = \frac{D}{d}, \]  

(7)

(3) The fatigue strength conditional constraint formula is

\[ n_{\text{ca}} = \frac{\tau_0 + 0.75\tau_{\text{min}}}{\tau_{\text{max}}} \geq n_{\text{f}}, \]  

(8)

where $n_{\text{ca}}$ is the calculation safety factor, $n_{\text{f}}$ is the design safety factor, $\tau_0$ is the pulsating cyclic fatigue limit of the steel wires, and $\tau_{\text{min}}$ is the minimum shear force in the springs.

(4) In order to avoid resonance phenomena during spring operation, it is necessary to construct an inequality relationship between the operating frequency of the spring and the frequency of external load changes, so the formula for the constraint condition of no resonance is

\[ f = 3.65 \times 10^5 \frac{d}{nD^2} \geq 10f_r, \]  

(9)

where $f$ is the natural frequency of the spring, $f_r$ is the frequency of external load changes, and $n$ is the effective number of turns.

(5) In order to maintain the stability of the spring during operation, it is necessary to limit the length-to-diameter ratio according to different working conditions of the spring. The stability condition constraint formula is

\[ b = \frac{(n - 0.5)d + 1.1\lambda_{\text{max}}}{D} \]  

(10)

When both ends of the spring are fixed, $b$ is required to be 5.3 or less; when one end is fixed and the other end is free to expand and contract, $b$ is required to be 3.7 or less; when both ends of the spring are free to expand and contract, $b$ is required to be 2.6 or less.

(6) The coil of the springs is constrained by the $C$:

\[ 4 \leq C = \frac{D}{d} \leq 9. \]  

(11)

2.1.2. Miniature Universal Circuit Breaker Model Construction. Because the switching force required for the universal circuit breakers is larger, two nested springs are used to provide the closing force. The density of carbon steel wires and spring wires is $\rho_1 = 7.8 \times 10^3$ kg/m$^3$, the shear elastic modulus of springs is $g = 8 \times 10^6$ MPa, and the diameters of outer and inner layers of spring wires are $d_1$ and $d_2$, respectively. The numbers of effective rings are $n_1$ and $n_2$, respectively. The middle diameters are $D_1$ and $D_2$, respectively.

The diameters of the springs, the numbers of effective rings, and the middle diameters are set as independent variables, that is,

\[ x = [d_1, n_1, D_1, d_2, n_2, D_2]^T = [x_1, x_2, x_3, x_4, x_5, x_6]^T. \]  

(12)

The corresponding objective function can be established according to the mass and volume formula:

\[ f(x) = \omega_1M(x) + \omega_2V(x). \]  

(13)

From the above formula,

\[ M(x) = 1.92 \times 10^{-5} \left[x_1^2(x_2 + 2)x_3 + x_1^2(x_5 + 2)x_6\right], \]  

\[ V(x) = 423.9 \times \left(x_1^4 + x_1^4\right) + 1.18 \times \left(x_1x_2^3 + x_4x_6^3\right), \]  

(14)

where $M(x)$ is the total mass of inner and outer springs, $V(x)$ is the total volume of inner and outer springs, and $\omega_1$ and $\omega_2$ are the weight coefficients of mass and volume, respectively. Through experimental analysis, when $\omega_1 = \omega_2 = 0.5$, the mass and volume of the contact spring obtained are the smallest.

2.2. Low Energy Consumption and High-Breaking Optimization Model of Universal Circuit Breaker

2.2.1. Low Energy Consumption Optimization Model for Universal Circuit Breakers. During the entire power transmission process of the low-voltage power distribution
system, about 30 to 40% of the power is consumed. The function of transformers, motors, and main universal circuit breakers is also the main reason for energy consumption. In order to reduce power consumption, it is necessary to select the appropriate number and capacity of transformers according to the actual situation of the power load to ensure that it is in a low energy consumption area. In the process of power supply, it can reduce the energy consumption by providing appropriate supply voltage and increasing the power of the low-voltage distribution system accordingly.

The calculation of the internal power consumption of the universal circuit breaker by the International Electrotechnical Standard is as follows [28]:

\[
W = \sum_{k=1}^{k=p} I_n^2 Z \cos \phi,
\]

where \( p \) is the number of phases, \( k \) is the number of stages, \( I_n \) is the rated current (A) of the universal circuit breaker, \( Z = R + X \), and \( \cos \phi \) is the phase deviation angle of the internal circuit.

Since the effect of impedance is negligible, formula (15) can be simplified to

\[
W = \sum_{k=1}^{k=p} I_n^2 R \cos \phi,
\]

where the single-contact resistance calculation formula is

\[
R = \rho_2 \frac{l}{S}
\]

where \( \rho_2 \) is the resistivity. Generally, when the length \( l \) is constant, using a plurality of copper braids with a cross-sectional area to increase the cross-sectional area \( S \), the resistance value \( R \) will decrease. The number of contacts is now \( t \). When the number of contacts is greater than \( l \), the total impedance is

\[
\frac{1}{Z} = \sum_{i=2}^{l} \frac{1}{R_i} = \sum_{i=2}^{l} \frac{1}{R}
\]

When the amount of consumables for a single contact is \( v \), the generalized objective function of the energy consumption of the universal circuit breaker can be established as

\[
f_{1} = \sum_{k=1}^{p} I_n^2 \cos \phi \frac{1}{\sum_{i=2}^{l} 1/R_i} + r_1^{(k)} ln (tv) + r_2^{(k)} \sum_{i=2}^{l} 1/R
\]

where \( r_1 \) and \( r_2 \) are punishment factors, and the general value ranges from 0.02 to 0.2.

2.2.2. Universal Circuit Breaker High-Breaking Optimization Model. Due to the action of the contact spring, the contact surface will undergo a certain deformation during the process of pressing the moving and static contacts. The resulting contact with the metal is achieved between a few scattered points. So, under microconditions, current flows through electrical contact. In order to facilitate the study, we consider the macroconditions, assuming that these scattered points are a plane, which results in the phenomenon of current contraction and concentration. This phenomenon causes the horizontal component of the current between the dynamic and static contacts to form an electromotive force [29, 30]. The force is called the Holm force and can be expressed as

\[
F_H = \frac{\mu_0 i^2}{4\pi} \ln \left( \frac{R_1}{r} \right),
\]

where \( i \) is the current passing through the contact, \( \mu_0 \) is the vacuum permeability, the value is \( 4\pi \times 10^{-7} \), \( R_1 \) is the contact radius, and \( r \) is the contact point radius.

The contact point radius is determined by factors such as contact pressure and contact material and can be expressed as

\[
r = \frac{F_k}{\pi \cdot \xi \cdot H}
\]

where \( F_k \) is the contact pressure, \( \xi \) is the contact coefficient and ranges from 0.3 to 0.6, and \( H \) is the Brinell hardness of the contact material, for example, the Brinell hardness of the silver material is 900 N/mm².

When the contact system is in the closed state, in addition to the Holm force caused by the current contraction, the electric repulsive force received by the dynamic and static contacts also has the Lorentz force generated by the conductive circuit of the contact.

In order to facilitate analysis and research, the Lorentz force on the conductive circuit of the contact is regarded as the electromotive force between two finite parallel conductors, which can be approximately expressed as [31]

\[
F_L = \frac{\mu_0 k L^2}{4\pi m}
\]

where \( k \) is the loop coefficient.

The loop coefficient \( k \) is related to the shape and length of the conductor and is inversely proportional to the distance between two finite parallel conductors. For two parallel finite-length linear conductors \( I_1 \) and \( I_2 \), the length of the parallel guide rod is \( L \), the distance between the conductors is \( m \), and the current flowing through the conductor is \( i \). At this time, the loop coefficient \( k \) can be expressed as

\[
k = \frac{2L}{m}
\]

Substituting formula (23) into formula (22), the Lorentz force can be expressed as

\[
F_L = \frac{\mu_0 m k L^2}{4\pi}
\]

Combining formulas (22) and (24), we can construct a mathematical model for the high breaking of a universal circuit breaker and find the maximum value of the electric force. In theory, it is the minimum value of the reciprocal of the electric force. Therefore, the following mathematical model is obtained:
where $\beta_1$ and $\beta_2$ are internal parameters of the universal circuit breaker, $\beta_1 + \beta_2 = 1$, $i$ is the current, $R_i$ is the contact radius, and $\xi$ is the contact coefficient.

2.3. Construction of Comprehensive Optimization Model for Universal Circuit Breaker. In the optimization design of the universal circuit breaker, we should not only consider the miniaturization of the universal circuit breaker but also consider the energy consumption and breaking capacity of the universal circuit breaker. Therefore, on the basis of the universal circuit breaker miniaturization model, we combined the universal circuit breaker’s low energy consumption model and high-segmentation model to construct a comprehensive optimization model for designing universal circuit breakers. The minimum mass and volume of the spring can be used as the optimization target.

According to formulas (13), (19), and (25), and combining the relationships between them, we can get the overall optimization objective function as

$$f = \varepsilon_1 \left[ \sum_{i=1}^{n} I_i^2 \cos \varphi \frac{1}{\sum_{i=2}^{n} (1/R_i) + r_1^{(k)} \ln (tv) + r_2^{(k)} \sum_{i=2}^{n} \left( \frac{1}{R_i} \right)} \right]$$

$$+ \varepsilon_2 \left[ \frac{1}{\beta_1 (\mu_0 i^2/4\pi) \ln (R_1/r) + \beta_2 (\mu_0 i^2/2L/m) r^2} \right]$$

$$+ \varepsilon_3 \left[ w_1 \frac{1}{4\pi} \pi^2 d^2 (n+2) D + w_2 \pi (D/2) H \right],$$

(26)

where $\varepsilon_1$, $\varepsilon_2$, and $\varepsilon_3$ are nonnegative weight coefficients in the objective function and $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 1$.

3. Intelligent Optimization Algorithm Design

3.1. Basic Gray Wolf Optimization Algorithm. Wolves belong to a fairly intelligent group of animals in nature. They are mainly gregarious. They hunt and kill prey by tracking, hunting, encircling, and finally attacking the target. Generally speaking, the gray wolf population is 5 to 12 as a whole. They live together and hunt together.

The hierarchical mechanism of the population in the gray wolf optimization algorithm is very strict, as shown in Figure 2.

In Figure 2, the head wolf at the top of the pyramid is called $\alpha$. Its main function is to make decisions about hunting behavior, habitat, and food distribution. It is not necessarily the best wolf, but it is the best leader. The wolf on the second level of the pyramid is called $\beta$. If $\alpha$ is missing from the wolf pack, then $\beta$ is the successor and helps to make a decision. At the third level of the pyramid is $\delta$, which listens to the instructions of $\alpha$ and $\beta$ and is mainly responsible for reconnaissance and alerting. Among them, $\alpha$ and $\beta$, which are less adaptable, will be reduced to $\delta$. The wolf pack at the bottom of the pyramid is called $\omega$, which is mainly responsible for balancing the internal relationships of the population and obeying other wolf packs. This strict hierarchical mechanism can make the gray wolf hunt the prey more efficiently [32].

According to the gray wolf’s hierarchy, we can think that $\alpha$ represents the optimal solution, $\beta$ represents the superior solution, $\delta$ represents the suboptimal solution, and $\omega$ is the candidate solution set, which is converted into a mathematical model. The updated formula can be obtained as

$$D = |C \cdot X_p(t) - X(t)|,$$

$$X(t + 1) = X_p(t) - A \cdot D,$$

(27)

where $D$ is the distance between the gray wolf and the prey, $C$ is the coefficient, $X_p$ is the position of the prey, $t$ is the number of iterations, $X$ is the position of the gray wolf individual, and $A$ is the coefficient.

The relationship between the coefficients $A$ and $C$ can be obtained from the following formula:

$$A = 2a \cdot r_1 - a,$$

$$C = 2r_2,$$

(28)

(29)

where $r_1$ and $r_2$ represent random numbers on [0, 1] and $a$ is the convergence factor.

As the number of iterations increases, $a$ will linearly decrease from 2 to 0; the closer $a$ is to 2, the stronger the global search ability, to avoid falling into a local optimal solution; the closer $a$ is to 0, the stronger the local search ability, which will accelerate convergence.

In formula (28), when $|A| > 1$, the gray wolf population expands the search range and can search for better prey, which is a global search. When $|A| < 1$, the gray wolf population’s enclosing circle shrinks and belongs to local search.

When the gray wolf determines the position of the prey and surrounds the target, it is generally led by the head wolf,
that is, the optimal solution $a$, and the position of the prey by the optimal solution $\beta$ and the suboptimal solution $\delta$, and then the position information of the wolf group is updated. The update formula is as follows:

$$
\begin{align*}
D_a &= [C_1 a - X(t)], \\
D_\beta &= [C_2 \beta - X(t)], \\
D_\delta &= [C_3 \delta - X(t)],
\end{align*}
$$

where $X_a$ is the current position of $a$, $X_\beta$ is the current position of $\beta$, $X_\delta$ is the current position of $\delta$, $C_1$, $C_2$, and $C_3$ represent random vectors, and $X(t)$ represents the current position of the gray wolf.

The definition of the length and direction of the $\omega$ wolf’s advance towards $a$, $\beta$, and $\delta$ wolves is

$$
\begin{align*}
X_1 &= X_a - A_1 \cdot D_a, \\
X_2 &= X_\beta - A_2 \cdot D_\beta, \\
X_3 &= X_\delta - A_3 \cdot D_\delta.
\end{align*}
$$

The final position where gray wolf $\omega$ can be obtained is

$$
X(t + 1) = \frac{(X_1 + X_2 + X_3)}{3}.
$$

3.2. Improved Gray Wolf Optimization Algorithm. Due to the shortcomings of the gray wolf optimization algorithm, such as slow convergence speed, low solution accuracy, and easily to fall into local minimum, we propose to improve the GWO algorithm.

Aiming at the shortcoming of GWO algorithm, the cloud model is introduced adjusting the size of the convergence factor $a$ according to the fitness of the gray wolf individual. The main role of $a$ is to balance the local search and global search capabilities and avoid falling into the local optimal solution.

The adjustment strategy of $A$ can be based on the idea of golden section. In the $k$-th iteration, $n$ gray wolf individuals in the gray wolf population are sorted from small to large according to the fitness value, and then the fitness value of the gray wolf population is defined. The golden section is

$$
 f_{\text{golden}}(k) = f_{\text{floor}}(0.618 \cdot n)(k).
$$

At this time, the gold fitness of $n_1$ gray wolf individuals with fitness greater than $f_{\text{golden}}$ is $f_{\text{better}}(k) = f_{\text{floor}}(0.618 \cdot n_1)(k)$ and the gold fitness of $n_2$ gray wolf individuals with fitness less than $a$ is $f_{\text{worse}}(k) = f_{\text{floor}}(0.618 \cdot n_2)(k)$. According to the two dividing lines $f_{\text{better}}(k)$ and $f_{\text{worse}}(k)$, the gray wolf divided into 3 subgroups. If the fitness value $m$ of the current gray wolf individual $i$ is greater than $n$, it means that some gray wolf individuals are close to the optimal solution, which accelerates the local convergence speed. It is not necessary to perform a global search. At this time, $a = 0$. If the fitness $f_i(k)$ of the gray wolf individual $i$ is less than $f_{\text{worse}}(k)$, the global search capability is enhanced and $a = 2$. If $f_{\text{worse}}(k) < f_i(k) < f_{\text{better}}(k)$, the convergence factor $a$ now is as follows:

$$
a = 2 - 2 \times e^{(-\left(f_i(k) - \text{EX}\right)^2/2(\text{En'})^2)},
$$

where EX is the expected value, En is the entropy value, and He is the super entropy value. The expressions are as follows:

$$
\begin{align*}
\text{EX} &= f_{\text{best}}(k), \\
\text{En} &= \frac{(f_{\text{better}}(k) - f_{\text{best}}(k))}{b_2}, \\
\text{He} &= \frac{\text{En}}{b_2},
\end{align*}
$$

where $b_1 = b_2 = 2$ and $\text{En'} = \text{normrnd}(\text{En}, \text{He})$.

During the iterative process, the $\omega$ wolf is approaching the three wolves $a$, $\beta$, and $\delta$, and it is easy to fall into a local minimum. Therefore, formula (32) is linearly weighted, that is, a weighting strategy is introduced to avoid falling into local minima:

$$
X(t + 1) = \frac{(w_1 X_1 + w_2 X_2 + w_3 X_3)}{3}.
$$

Here,

$$
\begin{align*}
w_1 &= \frac{X_1}{X_1 + X_2 + X_3}, \\
w_2 &= \frac{X_2}{X_1 + X_2 + X_3}, \\
w_3 &= \frac{X_3}{X_1 + X_2 + X_3}.
\end{align*}
$$

After introducing the cloud model and weight strategy, the improved GWO algorithm is named cloud model-weight GWO algorithm (CW-GWO).

The specific implementation steps of the CW-GWO algorithm are as follows:

Step 1: initialize the population. Set the relevant parameter values, the number of populations, the maximum number of iterations, and so on.
3.3. Performance Test and Analysis of CW-GWO Algorithm. To verify the feasibility and effectiveness of the algorithm, classic test functions are used. To avoid accidents, four different types of classic test functions were selected for the analysis of the CW-GWO algorithm. Test function expressions are shown in Table 1, so, for experimental environment: a Windows 10 system, processor model Intel (R) Core (TM) i5-5200U, main frequency 2.20GHZ, memory 4.0GB, MATLAB R2015b, was used. In MATLAB (R) Comprehensive Optimization Effect of the Universal Circuit Breaker

4.1. Comprehensive Optimization Design Steps of Universal Circuit Breaker. The comprehensive optimization design steps of the universal circuit breaker based on the intelligent optimization algorithm are as follows:

Step 1: according to the design requirements of the universal circuit breaker, the parameters that need to be designed are determined, such as the decreasing penalty factor, the contact resistance value, the number of contacts, the number of consumables, the phase deviation angle of the internal circuit, the contact radius, the contact coefficient, the current, spring diameter, and the effective number of spring turns.

Step 2: the universal circuit breaker miniaturization model, low energy consumption model, and high-breaking model are built, respectively.

Step 3: the comprehensive optimization model of the universal circuit breaker is constructed, and the determination of the coefficient can be selected by the empirical method or the grid method.

Step 4: according to the objective optimization function, a fitness function is established.

Step 5: the intelligent optimization algorithm is used for iterative optimization to obtain the parameter values of the comprehensive design of the universal circuit breaker.

4.2. Experiment and Analysis. In order to verify the comprehensive optimization effect of the universal circuit
breaker, the following two experimental studies are mainly performed on the universal circuit breaker of the model HSW6 series. The improved CW-GWO algorithm is used to optimize the design and the parameters such as decreasing penalty factor, contact resistance value, and contact parameters such as number of consumables, phase deviation angle of internal circuit, contact radius, current, spring diameter, and effective number of spring turns. For comparative analysis, the APSO algorithm, ABC algorithm, and CDE algorithm are used for optimization design.

4.2.1. Experiment 1. The parameter settings are as follows:

(a) Miniaturization: the value range of the spring diameter is 0.4~3 mm, the value range of the working circle is 8~20, the middle diameter of the spring is 3~25 mm, the safety factor of the spring design is 1.5, the forced vibration frequency is 4 Hz, and the minimum deformation is 0.1, which is 1000 N/mm². The maximum working load of the spring is 70 N, and the minimum working load of the spring is 30 N.

| Function name | Expression | Search interval | The optimal value |
|---------------|------------|-----------------|-------------------|
| Sphere        | $f_1(x) = \sum_{i=1}^{D} x_i^2$ | $[-100, 100]$ | 0                 |
| Schwefel2.22  | $f_2(x) = \sum_{i=1}^{D} |x_i| - \prod_{i=1}^{D} |x_i|$ | $[-100, 100]$ | 0                 |
| Rosenbrock    | $f_4(x) = \sum_{i=1}^{D} [100 \cdot (x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$ | $[-2.048, 2.048]$ | 0                 |
| Schaffer      | $f_7(x) = 0.5 + (\sin^2 \sqrt{\sum_{i=1}^{D} x_i^2} - 0.5/[1.0 + 0.001 (\sum_{i=1}^{D} x_i^2)])^2$ | $[-100, 100]$ | 0                 |

Figure 3: Iterative simulation diagram of sphere function optimization.

Figure 4: Schwefel2.22 function optimization iterative simulation diagram.

Figure 5: Iterative simulation diagram of Rosenbrock function optimization.
(b) Low energy consumption: decreasing coefficient of penalty factor, ranging from 0.02 to 0.2; single-contact resistance value ranging from 9 to 30; the phase deviation angle of the internal loop value ranging from 0.3 to 0.6; the number of contacts ranging from 11 to 20; consumable value range is 70 ∼ 125 kg; phase level, 3 phases; rated current is 2000 A.

(c) High breaking: there are 3 variables in total, among which the current ranges from 1000 to 4000 A, the contact radius ranges from 3 to 5 mm, and the phase deviation angle of the internal loop ranges from 0.3 to 0.6. Contact pressure is 2 N.

According to the comprehensive design model formula (26) of the universal circuit breaker, it is designed as a fitness function with coefficients of 0.3, 0.4, and 0.3, respectively. Four algorithms, APSO, ABC, CDE, and CW-GWO, are used for optimization. The fitness function is shown in Figure 7, and the optimization results are shown in Table 3.
As can be seen from Figure 7, when the comprehensive model of the universal circuit breaker is optimized, the fitness function value obtained by the CW-GWO algorithm is the best and the convergence speed is the fastest. It can be seen from Table 3 that under the requirements of low energy consumption and high segmentation, the miniaturization effect is relatively ideal.

4.2.2. Experiment 2. The parameter settings are as follows:

(a) Miniaturization: the value range of the spring diameter is 0.8–3 mm, the value range of the working circle is 5–20, the middle diameter of the spring is 6–30 mm, the safety factor of the spring design is 1.5, and the forced vibration frequency is 4 Hz. The minimum deformation is 0.1, which is 1000 N/mm². The maximum working load of the spring is 40 N, and the minimum working load of the spring is 20 N.

(b) Low energy consumption: decreasing coefficient of the penalty factor, ranging from 0.02 to 0.2; single-contact resistance value ranging from 11 to 28; the phase deviation angle of the internal loop value ranging from 0.3 to 0.32; number of contacts ranging from 7 to 20; consumable value range is 90–150 kg; phase level, four phases; and rated current is 3000 A.

(c) High breaking: there are 3 variables in total, among which the current ranges from 1000 to 4000 A, the contact radius ranges from 0.8 to 5 mm, and the phase deviation angle of the internal loop ranges from 0.3 to 0.6. Contact pressure is 6 N.

According to the comprehensive design model formula (26) of the universal circuit breaker, it is designed as a fitness function with coefficients of 0.3, 0.4, and 0.3, respectively. Four algorithms, APSO, ABC, CDE, and CW-GWO, are used for optimization. The fitness function is shown in Figure 8, and the optimization results are shown in Table 4.

| Optimal parameter                  | The optimal value |
|------------------------------------|-------------------|
| Spring diameter $d$ (mm)           | 0.8               |
| Number of working circles $n$      | 15.28             |
| Spring middle diameter $D$ (mm)    | 4.6               |
| Diminishing penalty factors $r_1, r_2 (r_1 = r_2)$ | 0.02, 0.02 |
| Single-contact resistance $R$ ($\mu\Omega$) | 18               |
| Phase angle of internal loop $\cos \phi$ | 0.3               |
| Number of contacts                 | 15                |
| Consumables (kg)                   | 90                |
| Current $i$ (A)                    | 2000              |
| Contact radius $R_1$ (mm)          | 3                 |
| Contact coefficient $\xi$          | 0.59              |

As can be seen from Figure 7, when the comprehensive model of the universal circuit breaker is optimized, the fitness function value obtained by the CW-GWO algorithm is the best and the convergence speed is the fastest. It can be seen from Table 3 that under the requirements of low energy consumption and high segmentation, the miniaturization effect is relatively ideal.
requirements of low energy consumption and high segmentation, the miniaturization effect is also ideal.

In summary, the comprehensive optimization design method of universal circuit breakers proposed in this paper is feasible and can obtain high-performance parameter indicators of universal circuit breakers and greatly improve the design accuracy and efficiency of universal circuit breakers.

5. Conclusions

By using the gray wolf optimization algorithm to study the optimal design of the universal circuit breaker, we can draw the following conclusions.

Firstly, in the miniaturization design of the universal circuit breaker, the energy consumption and breaking capacity of the universal circuit breaker must be considered. Therefore, based on the analysis of the miniaturization model, a low energy consumption model and a high-segmentation model are combined to construct a universal circuit breaker synthesis optimization model.

Secondly, in the study of the gray wolf optimization algorithm, in order to overcome the slow convergence speed, the introduction of the cloud model can balance the local search and global search capabilities and the introduction of the weighting strategy can avoid local minima. Therefore, an improved gray wolf optimization algorithm (CW-GWO) based on the cloud model and weight strategy is proposed.

Finally, the improved gray wolf optimization algorithm is applied to the optimization solution of the comprehensive model of the universal circuit breaker, and the high-performance parameter indicators of the universal circuit breaker can be obtained. The experimental results show that the method proposed in this paper is practical and greatly improves the design accuracy and efficiency of the circuit breaker.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (no. U1813222), Tianjin Natural Science Foundation (no. 18JCYBJC16500), and Key Research and Development Project from Hebei Province (no. 19210404D).

References

[1] A. Gholian, H. Mohsenian-Rad, and Y. Hua, "Optimal industrial load control in smart grid," *IEEE Transactions on Smart Grid*, vol. 7, no. 5, pp. 2305–2316, 2016.
[2] F. Liu, W. Liu, X. Zha, H. Yang, and K. Feng, "Solid-state circuit breaker snubber design for transient overvoltage suppression at bus fault interruption in low-voltage DC microgrid," *IEEE Transactions on Power Electronics*, vol. 32, no. 4, pp. 3007–3021, 2017.
[3] A. Maqsood, A. Overstreet, and K. Corzine, "Modified z-source DC circuit breaker topologies," *IEEE Transactions on Power Electronics*, vol. 31, no. 10, pp. 7394–7403, 2016.
[4] T. Zhu, Y. Zhan-Qing, R. Zeng et al., "Transient model and operation characteristics researches of hybrid DC circuit breaker," *Proceedings of the CSEE*, vol. 36, no. 1, pp. 18–30, 2016.
[5] X. Pei, O. Cwikowski, A. C. Smith, and M. Barnes, "Design and experimental tests of a superconducting hybrid DC circuit breaker," *IEEE Transactions on Applied Superconductivity*, vol. 28, no. 3, pp. 1–5, 2018.
[6] Z. Guo, Y. Yang, H. Liu et al., "Reliable life calculation of circuit breaker based on FTA and reliability function," in *Proceedings of the International Conference on High Voltage Engineering and Application*, pp. 732–737, September 2016, Chengdu, China.
[7] Y. Cai and K. Zhou, “A new detection method of contact pressure of universal circuit breaker and its application,”
[8] Bo Kai, B. Chen, X. Zhou et al., "Experimental research on breaking arc characteristics of DC miniature circuit breakers," Electrical Appliances and Energy Efficiency Management Technology, no. 22, pp. 35–39, 2018.

[9] A. Zhou, "Design of HUM8-63 moulded case circuit breaker with high-breaking low-voltage medium or small capacity," Electrotechnics Electric, no. 9, pp. 20–22, 2011.

[10] Y. Yang, X.-N. Xiao, H. Wang et al., "Overview and prospect of power system digital hybrid simulation technology," Electric Power Automation Equipment, vol. 37, no. 3, pp. 203–223, 2017.

[11] X.-W. Li, "Review of new technology for low voltage circuit breaker development," Electrical Appliances and Energy Efficiency Management Technology, no. 9, pp. 1–14, 2015.

[12] D.-G. Chen, "Development of low voltage electrical apparatus simulation and digital design technology," Electrical Appliances and Energy Efficiency Management Technology, no. 15, pp. 1–23, 2014.

[13] J. H. Lee, J.-W. Kim, J.-Y. Song, D.-W. Kim, Y.-J. Kim, and S.-Y. Jung, "Distance-based intelligent particle swarm optimization for optimal design of permanent magnet synchronous machine," IEEE Transactions on Magnetics, vol. 53, no. 6, pp. 1–4, 2017.

[14] Z.-Y. Zhao, Q. Quan, and K.-Y. Cai, "A modified profit-performance- reliability algorithm and its application to dynamic systems," Journal of Intelligent & Fuzzy Systems, vol. 32, no. 1, pp. 1–18, 2017.

[15] W. Chien, C.-C. Chiu, Y.-T. Cheng, S.-H. Liao, and H.-S. Yen, "Multi-objective optimization for UWB antenna array by APSO algorithm," Telecommunications Systems, vol. 64, no. 4, pp. 649–660, 2017.

[16] S. Dai, K. Xia, L. Zhang et al., "Optimal design of new multi-circuit breaker using CDE algorithm," High Voltage Apparatus, vol. 53, no. 12, pp. 188–194, 2017.

[17] X.-J. Shen, L. Wang, and D.-J. Han, "Application of BP neural network optimized by artificial bee colony in intrusion detection," Computer Engineering, vol. 42, no. 2, pp. 190–194, 2016.

[18] A. Kishor, P. K. Singh, and J. Prakash, "NSABC: non-dominated sorting based multi-objective artificial bee colony algorithm and its application in data clustering," Neurocomputing, vol. 216, pp. 514–533, 2016.

[19] Y. Zhong, J. Lin, L. Wang, and H. Zhang, "Hybrid discrete artificial bee colony algorithm with threshold acceptance criterion for traveling salesman problem," Information Sciences, vol. 421, no. 421, pp. 70–84, 2017.

[20] T. Wang, K. Xia, H. Tang et al., "A modified wolf pack algorithm for multi-constrained sparse linear array synthesis," International Journal of Antennas and Propagation, vol. 2020, pp. 1–12, 2020.

[21] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer,” Advances in Engineering Software, vol. 69, no. 3, pp. 46–61, 2014.

[22] J. Liu, L. Kuang, H. Yin et al., "K-means clustering algorithm optimized by gray wolf," China Science and Technology Paper, vol. 14, no. 7, pp. 778–782, 2019.

[23] Z. Teng, J. Lv, L. Guo et al., "An improved algorithm of hybrid gray wolf optimization based on Tent mapping,” Harbin: Journal of Harbin Institute of Technology, vol. 50, no. 11, pp. 40–49, 2018.