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Realizing the Improvement of the Reliability and Efficiency of Intelligent Electricity Inspection: IAOA-BP Algorithm for Anomaly Detection

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Abstract: Anomaly detection can improve the service level of the grid, effectively save human resources and reduce the operating cost of a power company. In this study, an improved arithmetic optimization-backpropagation (IAOA-BP) neural algorithm for an anomaly detection model was proposed for electricity inspection. The dynamic boundary strategy of the cosine control factor and the differential evolution operator are introduced into the arithmetic optimization algorithm (AOA) to obtain the improved arithmetic optimization algorithm (IAOA). The algorithm performance test proves that the IAOA has better solving ability and stability compared with the AOA, WOA, SCA, SOA and SSA. The IAOA was subsequently used to obtain the optimal weights and thresholds for BP. In the experimental phase, the proposed model is validated with electricity data provided by a power company. The results reveal that the overall determination accuracy using the IAOA-BP algorithm remains above 96%, and compared with other algorithms, the IAOA-BP has a higher accuracy and can meet the requirements grid supervision. The power load data anomaly detection model proposed in this study has some implications that might suggest how power companies can promote grid business model transformation, improve economic efficiency, enhance management and improve service quality.

Keywords: electricity inspection; anomaly detection; improved arithmetic optimization algorithm; backpropagation neural network



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1. Introduction

Electricity consumption inspection is an important part of power marketing work, which is of great significance to improving the management level and economic efficiency of enterprises, and regulating the power consumption behavior of customers [1] (Ahir et al., 2022). With the rapid development and progress of the economy and society, the smart grid is developing rapidly [2] (Kim et al., 2021). The smart grid is a grid that realizes panoramic operation information, networked data transmission, dynamic safety assessment, refined dispatching decision, automated operation control, and optimized machine and network coordination, and ensures a safe and reliable, flexible and coordinated, high-quality and efficient, and economically and environmentally friendly grid operation. In existing projects and future plans, various countries have invested significant human and financial resources in the development of smart grids [3] (Alabe et al., 2022). The increased intelligence of the power system has led to the timely and efficient collection of a wide variety of power data from a variety of sources [4] (Gaggero et al., 2022). These data originate from every node of the power supply system and are characterized by high dimensionality, multiple types and large volumes [5] (Chen et al., 2022). There are

many sources of power data, which mainly come from power production, generation, transmission, substations, distribution and consumption [6] (Mari et al., 2021). They can be broadly divided into three categories: firstly, power enterprise management data; secondly, power enterprise marketing data; and thirdly, power grid operation and equipment testing data [7] (Moure-Garrido et al., 2022). However, the power network is so large and the operating conditions are so complex that a small power failure problem can lead to a local grid failure [8] (Lee et al., 2022). In addition, abnormal power consumption behavior can cause a chain reaction and threaten the safety of the entire power grid [9] (Lei et al., 2023). Therefore, we must monitor the operational status of the power grid, conduct real-time detection of abnormal users, and conduct timely on-site inspections to eliminate safety hazards when abnormal power usage is detected. Anomaly data detection is an important support for the safe operation of the power grid [10]. In the distribution network, the use of anomaly detection methods can identify various abnormal states affecting electrical energy and identify the source so that losses can be stopped in time [11] (Oh et al., 2022). For equipment monitoring, anomaly detection can help check the operating status of equipment and effectively ensure its stable operation [12] (OpreaBara, 2021). For intelligent power systems, anomaly detection can improve the service level of the grid, effectively saving human resources, reducing operating costs and enabling the grid to operate more economically [13] (Pan et al., 2022).

2. Literature Review

The main causes of outliers in power data are caused by different sources of data, different statistical calibers of data, equipment failures, missing data master attributes, problems such as abnormal power usage behavior and the lack of standardized rules for storing power data [12,14]. Some outliers hide information related to the occurrence of abnormal situations in the system, and these data can be used to identify where the faults in the grid lie and eliminate them in a timely manner, and to provide methods to solve the abnormal situations, such as equipment fault detection and abnormal user behavior [15,16] (Wang et al., 2020; Wang et al., 2019). The data can be used to detect and analyze abnormalities in the grid and to reduce power losses [17] (Y. Peng et al., 2021). The application of effective abnormality detection means that the abnormal state of electrical energy can be monitored, the sources of power quality can be identified and eliminated, the spread of faults can be prevented, and power losses can be reduced. For equipment monitoring, specifically, abnormality detection helps to check the operational status of equipment and ensure stable operation [18–20].

The existing research can be broadly categorized into two types of detection methods: (1) traditional detection methods; (2) artificial intelligence-based detection methods [2] (Kim et al., 2021). The traditional power load anomaly data detection methods are generally based on human experience, state estimation, load curve similarity and load change rate [21] (Li et al., 2020). Usually, the experience-based detection method is a means to achieve the identification of abnormal load data by the power staff, using the accumulated relevant knowledge and work experience, among other subjective methods, which is rarely used at present due to low efficiency and many other human factors [6,22] (Maamar et al., 2019; Mari et al., 2021). Artificial intelligence-based detection methods, such as artificial neural networks and support vector machines, have achieved better detection results [23] (OpreaBara, 2021).

With the advent of grid intelligence, load clustering methods are increasingly being explored [24] (Park et al., 2020). The use of clustering algorithms for multiple clustering of loads, the selection of the best model based on the clustering evaluation index and this model's application are common tools. Leong et al. identified a method using Euclidean distance as a similarity criterion, but it was difficult to identify load curves with similar distances and different shapes [25] (Leong et al., 2016). Panapakidis et al. adopted a fuzzy clustering approach to classify load curves, and used cluster evaluation metrics to determine the optimal number of clusters [26] (Panapakidis et al., 2017). Traditional

clustering methods often have some shortcomings and need to be optimized to improve the model, e.g., through optimization algorithms to find the best clustering centers [27,28] (Abul Hasan et al., 2011; Beyan et al., 2015). Based on fuzzy clustering and systematic clustering, some scholars have taken the approach of quadratic clustering and innovated it to explore customer electricity consumption characteristics from different directions [29] (Xiao et al., 2020). Others combine fuzzy C-means with K-means clustering algorithms and add variational modal decomposition algorithms, with significantly improved clustering effects [30,31] (Qi et al., 2022; J.F. Zhang et al., 2021). The above methods all perform clustering in the original space, and as the data collected by smart meters gradually become more detailed, the dimensionality of the data obtained will become higher and higher, and the application of direct clustering will be constrained by the computational efficiency and eventually reduce the performance of clustering.

The detection of electricity anomalies is an important part of electricity inspection. The traditional way of detecting abnormal electricity consumption first requires the installation of equipment, such as metering boxes and smart meters, to prevent abnormal electricity consumption, and when the system detects an abnormality, it requires grid staff to visit the site to make a judgement based on sensor data using their experience, which takes a lot of time, manpower and economic costs [10,32] (Zhao et al., 2019; Zheng et al., 2021). After a long period of research and practice by scholars, artificial intelligence-based methods of detecting anomalies in electricity consumption have now been widely used in practice. Singh et al. proposed a decision tree-based method that feeds decision tree-processed data into a support vector machine classifier as input [33] (Singh et al., 2018). The scheme is capable of detecting and locating power theft at all levels of the transmission and distribution network in real time. Simulation results indicate that the algorithm has some real-time performance and improves the correctness of data anomaly checking to a certain extent. Wang et al. used an artificial neural network for power anomaly detection, and simulation experiments demonstrated that the method could significantly improve the efficiency of anomaly detection and help the company recover the cost of losses [15] (Wang et al., 2020). Pei et al. used a support vector machine (SVM) to collect load information from clients to detect anomalous behavior, and experiments show that its detection performance is superior to traditional methods [34] (Pei et al., 2022). Similarly, Yampikulsakul et al. investigated a least squares SVM approach to wind power system anomaly identification [35] (Yampikulsakul et al., 2014). An SVM-based anomaly detection algorithm is proposed by Wang et al; the results of the actual tests demonstrate the practicality and high accuracy of the proposed algorithm [16] (Wang et al., 2019). Tian et al. used an SVM to identify anomalies based on historical load data [36] (Tian et al., 2022). However, an SVM is only a simple probabilistic classifier, which has some limitations in dealing with complex data. Applying an artificial neural network to abnormal electricity usage detection can successfully extract features from a large amount of data and achieve better detection results.

Applying artificial intelligence technology to the detection of abnormal electricity consumption behavior can be a good way to extract features from a large amount of data and achieve better detection results [37,38] (Hossein Mohammadi Rouzbahani et al., 2021; H.M. Rouzbahani et al., 2023). Peng et al. proposed a network traffic anomaly detection algorithm with a backpropagation (BP) neural network algorithm and a Bayesian network. The results show that the method can not only detect anomalies but also handle them [39] (H. Peng et al., 2019). Zhang et al. proposed an anomaly detection algorithm based on a BP neural network. Simulation results show that the proposed algorithm can detect anomalies more accurately [10] (Y. Zhang et al., 2019). Similarly, Yang et al. proposed a BP neural network-based abnormal load detection model. The simulation results show that the detection model has better recognition accuracy [40] (Yang et al., 2023). Shang et al. proposed a BP neural network-based method for predicting electricity theft behavior. The simulation results verify that the method has certain practicality and effectiveness [41] (Shang et al., 2022).

A BP neural network is a kind of artificial intelligence technology. The gradient descent optimization algorithm is used in the neural network, and when the number of neurons increases, the target error function to be optimized becomes more complex, resulting in a longer error convergence time [21,42,43] (Yan Zhang et al., 2022; Zhong et al., 2014). Therefore, there is an urgent need to improve the parameter optimization process of the neural network and increase the training speed. Based on the above problems, this paper proposes an algorithm for detecting abnormal behavior in electricity consumption based on an improved arithmetic optimization algorithm for optimizing BP neural networks. The meaningful contributions of this study can be summarized as follows.

- An improved arithmetic optimization algorithm (IAOA) is proposed. Compared with the other algorithm, the IAOA has a stronger solving ability and efficiency.
- An improved arithmetic optimization algorithm-backpropagation (IAOA-BP) neural algorithm is proposed. The IAOA-BP algorithm is used for power data anomaly detection.
- The proposed IAOA-BP anomaly detection method maintains a high accuracy rate, which can improve the detection efficiency and reduce the operational cost of the business.

The rest of this study is organized as follows. Section 3 describes the IAOA-BP based anomaly detection method. Section 4 conducts simulation experiments and discusses them. Section 5 describes the contribution of the study and its limitations.

3. Improved Arithmetic Optimization Algorithm-Backpropagation Neural Algorithm

The Arithmetic Optimization Algorithm (AOA) is a new type of heuristic algorithm for solving engineering problems, which can simulate the behavior of a population to optimize numerical problems in an iterative manner. However, similarly to most heuristic algorithms, some improvements to the algorithm are needed to further enhance its solving power and improve its ability to jump out of the local optimum [44]. Therefore, how to improve the optimization ability of the algorithm has become a hot topic of concern for many researchers [45,46] (Ali et al., 2023; AliKamel et al., 2022; AliSalawudeen et al., 2022). The improved AOA (IAOA) is employed for optimizing a BP neural network. Next, this study will detail the IAOA-BP algorithm.

3.1. Arithmetic Optimization Algorithm

The AOA is a novel meta-inspired algorithm proposed by Laith Abualigah [47] (Abualigah et al., 2021). The AOA is inspired by the arithmetic operations add (A), subtract (S), multiply (M) and divide (D) in arithmetic problems. The multiply M and divide D operations allow for highly dispersed data for particle exploration and finding locations close to optimal solutions; the add A and subtract S operations allow for highly dense data for particle development and have the ability to avoid getting trapped in a local optimum and prevent stagnation late in the iteration. The exploration and exploitation operations of the particles in each iteration depend on the value of the mathematically optimized acceleration function (MOA), as follows.

$$MOA(iter) = MIN + iter \times (MAX - MIN) / Max_iter \quad (1)$$

where MAX and MIN are the maximum and minimum values of MOA , respectively; $iter$ denotes the current number of iterations; Max_iter denotes the number of iterations. The mathematical optimization probability (MOP) is the coefficient in the particle position update equation, which can be expressed as follows.

$$MOP(iter) = 1 - 1 / Max_iter^{1/\delta} \quad (2)$$

where δ is a sensitive parameter and is set to 5 in this experiment.

(1) Initialization

During initialization, we set the maximum iterations, the number of particles, the number of particle dimensions, the upper limit UB and the lower limit LB of the particle

positions. We randomly initialize the particle positions, calculate the optimal values and optimal positions and compute *MOA* and *MOP*.

(2) Exploration phase

If $r_1 > MOA$, then the algorithm exploration phase is entered. r_1 is a random number between (0,1). The update formula for the particle exploration operation is as follows.

$$x_{i,j}(iter + 1) = \begin{cases} best_j \div (MOP + \epsilon) \times w_j, & r_2 < 0.5 \\ best_j \times MOP \times w_j, & otherwise \end{cases} \quad (3)$$

where $best_j$ is the j th dimension of the optimal particle position; r_2 is a random number between (0,1); ϵ is a small positive number.

(3) Exploitation phase

If $r_1 \leq MOA$, the algorithm enters the development phase. The formula for updating the position of an individual is as follows.

$$x_{i,j}(iter + 1) = \begin{cases} best_j - (MOP + \epsilon) \times w_j, & r_3 < 0.5 \\ best_j + MOP \times w_j, & otherwise \end{cases} \quad (4)$$

where r_3 is a random number between (0,1). w_j can be calculated as follows.

$$w_j = ((ub_j - lb_j) \times \mu + lb_j) \quad (5)$$

where μ is to adjust the parameters of the search process and is set to 0.5 in this study.

3.2. Improved Arithmetic Optimization Algorithm

The AOA has a highly competitive output when solving simple models. However, it has disadvantages, such as slow convergence and the tendency to fall into localization in the later stages of the optimization search. Therefore, the arithmetic optimization algorithm needs to be improved in order to enhance the optimization-seeking ability and the convergence speed of the algorithm.

(1) Dynamic boundary strategy with cosine control factor

MOA is an important parameter that balances local optimization with global search. As the number of iterations increases, *MOA* increases linearly from 0.2 to 1, which makes it difficult to match the reality of the algorithmic optimization during the search. *MOA* is linearly increasing from 0.2 in the early iteration, resulting in the AOA not being able to explore more search space, and, thus, making the algorithm's global exploration capability insufficient. *MOA* assumes large values at the end of iterations, resulting in limited local evolution of the algorithm and slow convergence. In this study, in order to settle the problem, the *MOA* is reformulated. The reformulated *MOA* is as follows.

$$MOA = (Max - Min) \times (\cos(0.5\pi \times \frac{Iter}{Max_Iter})) + 0.5Min \quad (6)$$

(2) Differential evolution strategy

In order to improve the problem of the algorithm relying too heavily on the optimal solution, and to improve the solution accuracy of the algorithm, this paper introduces a differential evolution strategy in the AOA algorithm, which generates new individuals through mutation and crossover, and improves the search ability of the algorithm by comparing the individual fitness values before and after differential evolution. The process of implementation is as follows.

$$\vec{X}_m(it) = \vec{X}_{c3}(it) + F \cdot [\vec{X}_{c1}(it) - \vec{X}_{c2}(it)] \quad (7)$$

where $\vec{X}_{c1}(it)$, $\vec{X}_{c2}(it)$ and $\vec{X}_{c3}(it)$ are three randomly selected individuals; $\vec{X}_m(it)$ is the individual after mutation; F is a random number in the range $[0.2, 0.8]$.

Next, the current individual is crossed with the mutated individual to obtain the new individual, and the crossover expression is as follows.

$$\vec{X}_c(it) = \begin{cases} \vec{X}_m(it) & r_3 < P_c \\ \vec{X}_i(it) & r_3 \geq P_c \end{cases} \quad (8)$$

where $\vec{X}_c(it)$ is the l th dimensional variable of the current individual; $\vec{X}_m(it)$ is the l th dimensional variable of the variant individual; P_c is the crossover probability; r_3 is a random number in the range $[0, 1]$.

Finally, the optimal individual is selected by comparing the fitness of the individuals before and after the mutation, and the expression of the selection operation is as follows.

$$\vec{X}_i(it) = \begin{cases} \vec{X}_c(it) & f(\vec{X}_c(it)) < f(\vec{X}_i(it)) \\ \vec{X}_i(it) & f(\vec{X}_i(it)) \leq f(\vec{X}_c(it)) \end{cases} \quad (9)$$

where $f(\vec{X}_c(it))$ and $f(\vec{X}_i(it))$ indicate the individual fitness values before and after the mutation, respectively.

The IAOA was obtained by introducing a dynamic boundary strategy with the cosine control factor, and a differential evolution operator, to the AOA. The IAOA optimization process is as follows in Figure 1.

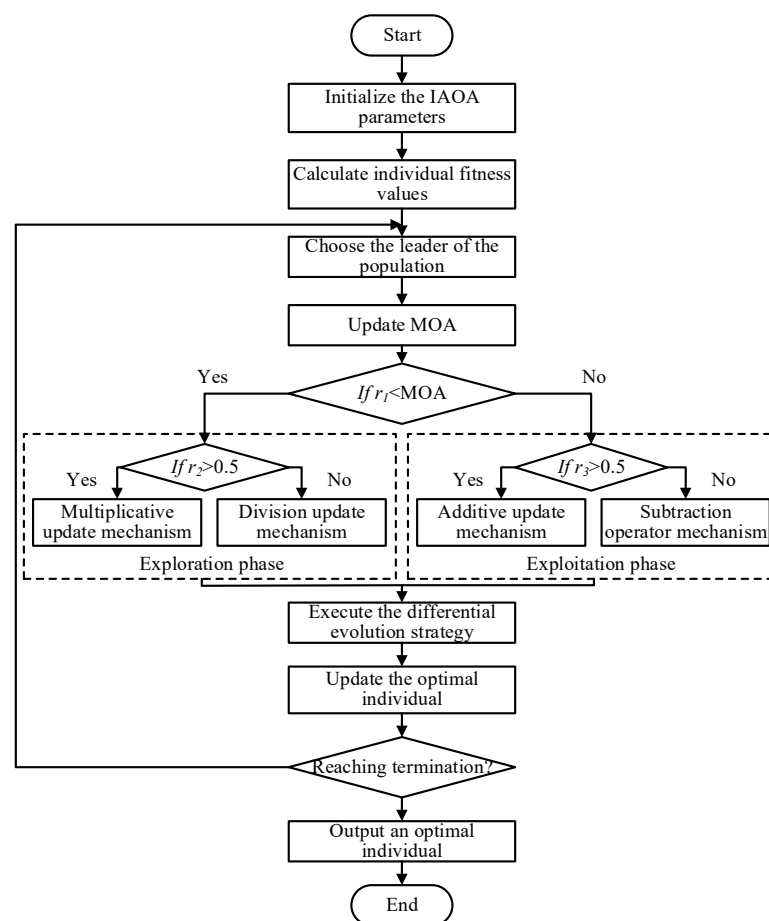


Figure 1. Flow chart of improved arithmetic optimization algorithm.

Performance Test of IAOA Algorithm

To improve the performance and stability of the algorithm, the IAOA is obtained by introducing a dynamic boundary strategy with the cosine control factor and a differential evolution operator to the AOA. To verify the convergence performance of the IAOA algorithm, a test of the convergence performance of the proposed IAOA algorithm was carried out on six benchmark functions and the results are compared with the AOA, the Salp Swarm Algorithm (SSA) [48] (Mirjalili et al., 2017), the Sine Cosine Algorithm (SCA) [49] (Mirjalili, 2016), the Seagull Optimization Algorithm (SOA) [50] (Dhiman et al., 2019) and the Whale Optimization Algorithm (WOA) [51] (Mirjalili et al., 2016). Table 1 shows the expressions, the variable intervals and the variable dimensions of the benchmark test functions, in which the f_4 – f_6 benchmark test functions are multi-peak test functions and the rest are single-peak test functions. All benchmark test functions have a variable dimension of 30 dimensions, and the variables under each test function take the same range of values. Typical three-dimensional diagrams of the single-peak and multi-peak test functions are presented in Figures 2 and 3. Table 2 displays the relevant parameter settings for the optimization algorithms. The experimental environment in this paper is a computer with Intel (R) Core (TM) i7-4720 HQ CPU, 2.60 GHz, 12 GB of RAM and a 64-bit Windows 10 operating system. The programming language is MATLAB, version R2021a.

Table 1. Benchmark functions.

Function	Dim	Range
$f_1 = \sum_{i=1}^D x_i^2$	30	$[-100, 100]$
$f_2 = \sum_{i=1}^D x_i + \prod_{i=1}^D x_i $	30	$[-10, 10]$
$f_3 = \sum_{i=1}^D \left(\sum_{j=1}^i x_j \right)^2$	30	$[-100, 100]$
$f_4 = \sum_{i=1}^D (x_i - 10 \cdot \cos(2\pi x_i) + 10)$	30	$[-5.12, 5.12]$
$f_5 = 20 \exp \left(-0.2 \sqrt{\frac{1}{30} \sum_{i=1}^D x_i^2} \right) + 20 - \exp \left(\frac{1}{30} \sum_{i=1}^D \cos(2\pi x_i) \right) + e$	30	$[-32, 32]$
$f_6 = \frac{\sum_{i=1}^D x_i^2}{4000} - \prod_{i=1}^D \cos \left(\frac{x_i}{\sqrt{i}} \right) + 1$	30	$[-600, 600]$

Table 2. Optimization algorithm parameter settings.

Algorithm	Parameters
SSA	$Np = 30$
SCA	$Np = 30, Ne = 2$
SOA	$Np = 30, f_c = 2$
WOA	$Np = 30, p = 0.5$
AOA	$Np = 30, a = 2, \mu = 0.499$
IAOA	$Np = 30, a = 2, \mu = 0.499$

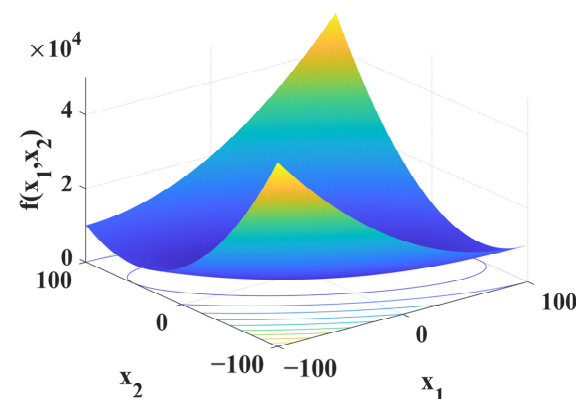


Figure 2. Three-dimensional diagram of typical unimodal test function.

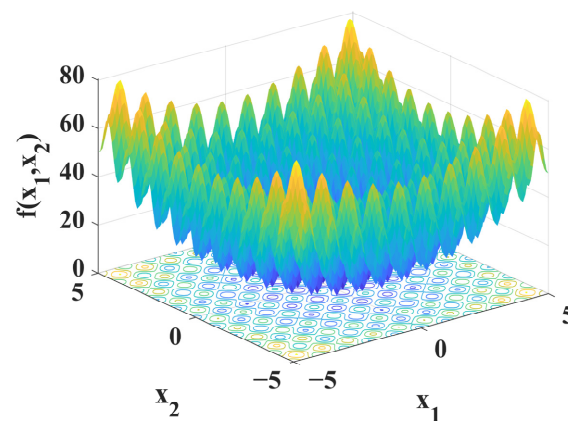


Figure 3. Three-dimensional diagram of typical multimodal test function.

A typical three-dimensional diagram of a single-peak test function is displayed in Figure 2. The single-peak test function has only one global optimum solution, and this test function is mainly used to check the convergence performance of the algorithm. For an intelligent optimization algorithm, if its final output differs significantly from the global optimal solution, it indicates that the convergence of the algorithm needs to be improved. Therefore, in this section, three single-peak test functions f_1 – f_3 are chosen to perform tests on the IAOA's optimization-seeking capability.

In this study, the capability of the algorithm to avoid falling into a local optimum is tested using a multi-peak test function, as shown in Figure 3, for a typical multi-peak test function three-dimensional diagram. Under the multi-peak test function, in addition to the global optimal solution, there are also a number of deceptive local optimum solutions, which will increase the optimization difficulty of the test function. If the algorithm is not enough to avoid falling into a local optimum, the algorithm will eventually converge to the local optimum solution. If the convergence capability of the algorithm is not sufficient, the output of the inner optimization model will be less satisfactory and will subsequently cause the model optimization to fail. Therefore, this section adopts a multi-peak test function to carry out a test of the convergence capability of the IAOA.

To avoid chance, all algorithms were run 30 times independently under each benchmark test function and the statistical algorithm output; the standard deviation; and the mean, minimum and maximum values of the optimization results are displayed in Table 3.

As shown in Table 3, the standard deviation, and the mean, minimum and maximum values obtained by the different optimization algorithms for the single-peaked and multi-peaked test functions are presented. For the f_1 – f_3 single-peak test functions, the standard deviation and the mean, optimum and maximum values obtained by the IAOA all reach zero, which indicates that the IAOA achieves the global optimum solution, and that the improved arithmetic optimization algorithm achieves an improvement in optimization-seeking ability. Similarly, the standard deviation obtained by the IAOA for the single-peak test functions is 0.00×10^0 , which also indicates that the IAOA's optimization-seeking performance is more stable.

As can be seen from Table 3, for the f_4 – f_6 multi-peak test functions, the standard deviation of the IAOA reaches 0.00×10^0 , 0.00×10^0 and 4.23×10^{-7} , respectively, which is at least one order of magnitude lower than that of the other algorithms, and proves the stable optimization-seeking ability of the IAOA. In addition, the IAOA's obtained mean, optimum and maximum values have a significant advantage over those of other algorithms, which demonstrates the IAOA's better search capability. Therefore, through the above algorithm performance test simulation experiments, the superior performance of the IAOA is verified, and the foundation is laid to use the IAOA to solve the optimal weights and thresholds of the BP neural network.

Table 3. Test results of each algorithm.

Function	Algorithm	Std	Mean	Min	Max
f_1	SSA	3.88×10^1	$4.92\text{E} \times 10^1$	5.81×10^0	1.76×10^2
	SCA	6.02×10^{-2}	1.56×10^{-2}	7.24×10^{-7}	3.17×10^{-1}
	SOA	1.73×10^{-2}	1.69×10^{-2}	2.51×10^{-3}	7.75×10^{-2}
	WOA	1.69×10^{-71}	3.65×10^{-72}	9.82×10^{-84}	9.13×10^{-71}
	AOA	1.57×10^{-112}	2.87×10^{-113}	0.00×10^0	8.62×10^{-112}
	IAOA	0.00×10^0	0.00×10^0	0.00×10^0	0.00×10^0
f_2	SSA	4.02×10^{-1}	9.87×10^{-2}	1.55×10^{-5}	2.18×10^0
	SCA	8.06×10^{-4}	6.08×10^{-4}	2.12×10^{-6}	3.88×10^{-3}
	SOA	7.06×10^{-3}	1.03×10^{-2}	2.67×10^{-3}	3.28×10^{-2}
	WOA	1.42×10^{-50}	5.66×10^{-51}	2.51×10^{-57}	5.87×10^{-50}
	AOA	1.05×10^{-10}	7.78×10^{-10}	2.24×10^{-9}	6.05×10^{-10}
	IAOA	0.00×10^0	0.00×10^0	0.00×10^0	$0.00\text{E} \times 10^0$
f_3	SSA	1.66×10^1	8.32×10^0	2.03×10^{-2}	8.28×10^1
	SCA	3.59×10^1	2.11×10^1	7.87×10^{-3}	1.43×10^2
	SOA	6.02×10^1	2.98×10^1	1.00×10^0	3.35×10^2
	WOA	2.04×10^4	8.15×10^4	4.57×10^4	1.33×10^5
	AOA	7.09×10^{-10}	1.20×10^{-7}	1.53×10^{-6}	2.88×10^{-7}
	IAOA	0.00×10^0	0.00×10^0	0.00×10^0	0.00×10^0
f_4	SSA	9.13×10^0	1.78×10^1	6.96×10^0	4.38×10^1
	SCA	1.07×10^1	7.56×10^0	1.51×10^{-4}	3.57×10^1
	SOA	1.36×10^1	2.28×10^1	5.07×10^0	6.15×10^1
	WOA	2.40×10^0	4.39×10^{-1}	0.00×10^0	1.32×10^1
	AOA	5.68×10^{-14}	1.93×10^0	3.48×10^1	6.60×10^0
	IAOA	0.00×10^0	0.00×10^0	0.00×10^0	0.00×10^0
f_5	SSA	1.13×10^0	9.25×10^{-1}	8.00×10^{-6}	3.57×10^0
	SCA	1.41×10^0	3.76×10^{-1}	6.59×10^{-4}	7.47×10^0
	SOA	1.62×10^{-3}	2.00×10^1	2.00×10^1	2.00×10^1
	WOA	1.97×10^{-14}	2.30×10^{-14}	8.88×10^{-16}	1.11×10^{-13}
	AOA	1.32×10^{-8}	1.86×10^1	2.00×10^1	5.06×10^0
	IAOA	0.00×10^0	8.88×10^{-16}	8.88×10^{-16}	8.88×10^{-16}
f_6	SSA	9.00×10^{-2}	1.52×10^{-1}	1.48×10^{-2}	3.27×10^{-1}
	SCA	1.96×10^{-1}	2.53×10^{-1}	7.12×10^{-4}	7.34×10^{-1}
	SOA	1.16×10^{-1}	1.41×10^{-1}	2.78×10^{-3}	4.20×10^{-1}
	WOA	1.03×10^{-1}	1.88×10^{-2}	0.00×10^0	5.64×10^{-1}
	AOA	1.11×10^{-15}	1.26×10^{-2}	8.42×10^{-2}	2.25×10^{-2}
	IAOA	4.23×10^{-7}	1.87×10^{-7}	0.00×10^0	2.07×10^{-6}

The single run times for all algorithms are shown in Table 4. There is not much difference between the runtime of the IAOA and the other algorithms.

Table 4. Running time statistics of the algorithms.

Algorithm	f_1	f_2	f_3	f_4	f_5	f_6
SSA	0.125132	0.078146	0.096693	0.098019	0.091074	0.084159
SCA	0.097549	0.094793	0.098377	0.107225	0.096317	0.085647
SOA	0.107971	0.071633	0.143617	0.116311	0.102076	0.115546
WOA	0.105432	0.084635	0.124563	0.0967565	0.096756	0.104534
AOA	0.098016	0.093391	0.107763	0.091656	0.089446	0.088593
IAOA	0.108016	0.103242	0.113242	0.101243	0.094353	0.090353

3.3. Backpropagation Neural Network

BP neural networks are modeled by mimicking the process of receiving, transmitting and storing information from the human brain, with powerful learning and feedback error correction capabilities [52] (Basheer et al., 2000). The output results are obtained by

establishing a layer-to-layer weight matrix through the layer-to-layer mapping relationship of the input parameters. The obtained results are compared with the design error, and if they meet the expectation, the settlement is executed, and if not, the implied layer weights are adjusted using the feedback error until the results are met. Considering the huge amount of data existing in the process of grid operation, this paper adopts a three-layer BP neural network with multiple inputs and single outputs as the evaluation model to achieve the mapping of m-dimensional inputs to n-dimensional outputs and to ensure the accuracy of data processing. Figure 4 shows the topology of the three-layer BP neural network.

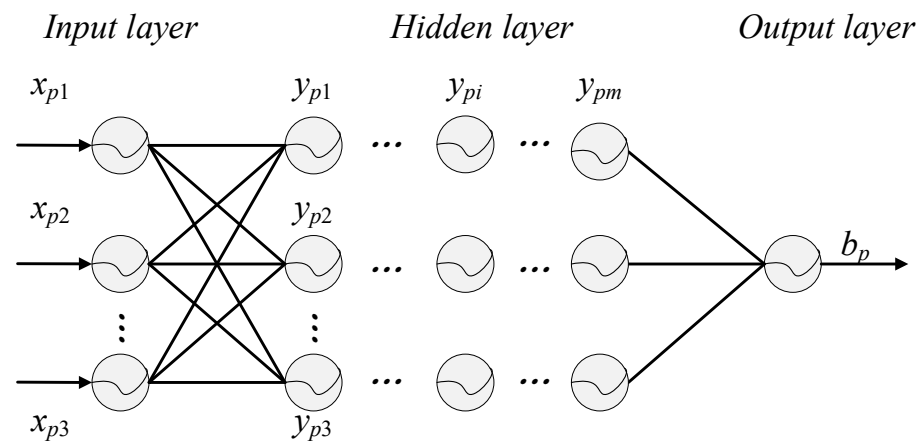


Figure 4. BP neural network topology, where x_{p1} , x_{p2} and x_{p3} denote input layer neurons; y_{p1} , y_{p2} and y_{p3} denote the hidden layer neurons; b_p indicates output.

For the purpose of overcoming the problem of selecting the initial threshold and the initial weights for the BP neural network, the IAOA is used in combination with the BP neural network to optimize the entire algorithmic network. In the optimization process of the BP neural network, the IAOA is employed to search for the optimal threshold and weights of the neural network. As the number of iterations increases, the optimal individual positions are obtained and used as the initial threshold and the initial weights of the BP neural network. The optimization process of IAOA-BP is shown in Figure 5.

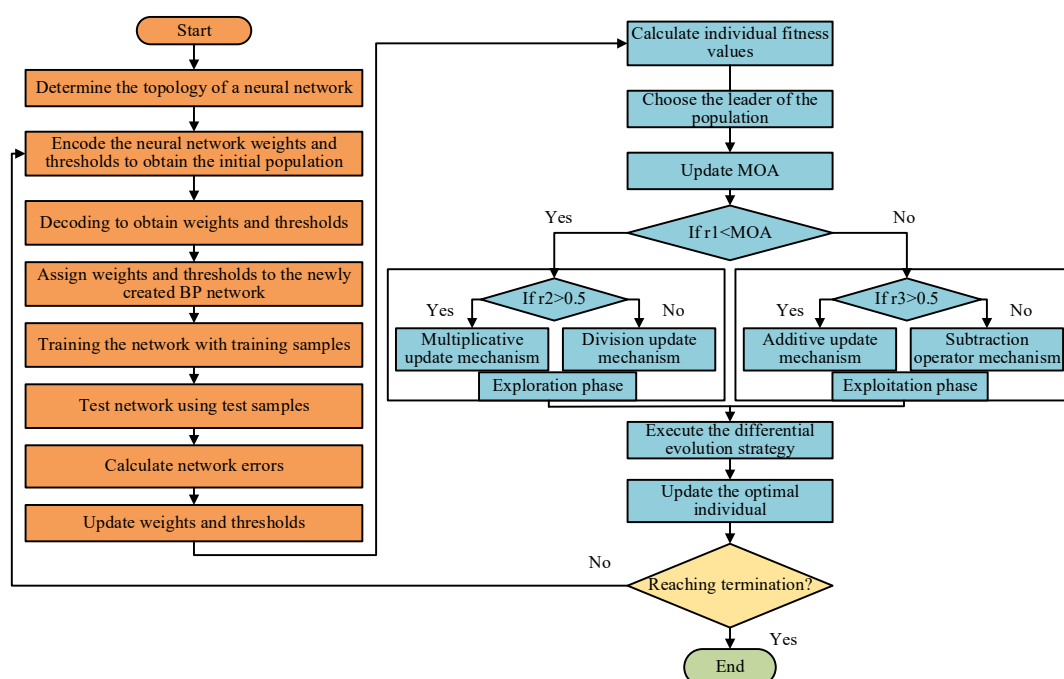


Figure 5. Specific flow chart of the IAOA-BP algorithm.

4. Implementation of the Proposed Approach

The electricity consumption data of a user in a single place for 5 years from January 2010 to December 2014 was selected to analyze suspected electricity theft. This user had committed electricity theft in October and November 2013 and was found to have paid for the electricity. However, in the four months from February to May 2014, there was another act of electricity theft, and the electricity consumption was normal after being detected. Depending on the customer's electricity consumption characteristics, electricity consumption parameters such as line loss, current unbalance ratio, power factor and voltage unbalance ratio will change when there are load data anomalies. In this study, these electrical parameters are used as input variables. Using the IAOA-BP neural network algorithm, the final output is expected to be of three types: no suspicion of electricity theft, general suspicion of electricity theft and major suspicion of electricity theft. The final output index is in the range of [0, 0.5] for no suspicion of electricity theft, in the range of [0.5, 0.8] for general suspicion of electricity theft and in the range of [0.8, 1] for major suspicion of electricity theft, which needs to be examined.

To ensure a high convergence rate during training, all the input data are normalized in this study. In this paper, we restrict the data to the interval [0, 1], and the transformation equation used is as follows.

$$y'_i = \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \quad (10)$$

where y_i is the input data; y'_i is the normalized data; $y_{\min}$ and $y_{\max}$ are the minimum and maximum data of the sample, respectively. The normalized data are shown in Table 5.

Table 5. Normalized customer electricity consumption data.

Total Electricity	Current Value	Voltage Value	Power Factor	Phase Angle	Line Loss	Current Unbalance Ratio	Voltage Unbalance Ratio
0.41502	0.18201	0.22729	0.416	0.830	0.96421	0.408	0.643
0.34192	0.25433	0.13801	0.079	0.874	0.94730	0.359	0.182
0.39369	0.26501	0.91987	0.361	0.852	0.94161	0.863	0.765
0.25005	0.26799	0.741	0.182	0.950	0.89841	0.978	0.886
0.86918	0.72499	0.03900	0.963	0.049	0.05311	0.766	0.511
0.74992	1.00101	0.66499	0.98	0.07	0.04450	0.867	0.907
0.81814	0.91599	0.02477	0.688	0.058	0.03551	0.944	0.704
0.34495	0.17401	0.50099	0.311	0.811	0.91899	0.676	0.805
0.61899	0.70601	0.23355	0.470	0.270	0.24510	0.734	0.498
0.13466	0.38411	0.29201	0.089	0.597	0.70893	0.466	0.594

Based on the constructed model, a BP neural network model with two implicit layers was built using Matlab and the learning accuracy was set to 10×10^{-5} . The input normalized data was iterated until the accuracy requirement was met. The suspected customer electricity consumption after the analysis of the BP neural network algorithm with two hidden layers is shown in Figure 6. The suspected customer electricity theft coefficients for August 2013 to September 2013 and March 2014 to June 2014 are shown in Table 4. The coefficient of suspicion of electricity theft is above 0.9, which suggests a significant suspicion of electricity theft, and is the same as the actual situation; meanwhile, there is no suspicion of electricity theft from customers in all other months, which is also in line with the actual situation.

For the purpose of verifying the reliability and effectiveness of the IAOA-BP algorithm for the detection of abnormal electric load data, the abnormality detection results are compared with the AOA-BP, SCA-BP, SSA-BP, WOA-BP and SOA-BP algorithms. Figure 6 shows the detection results of abnormal load data for the above algorithms. From Figure 6, it can be seen that among the six anomaly detection algorithms, the algorithm proposed in this paper has the highest accuracy in anomaly load data detection with an accuracy of

96.67%, followed by the WOA-BP, SCA-BP and SSA-BP algorithms with an accuracy of 93.33%, and the AOA-BP and SOA-BP algorithms with an accuracy of 91.67%. From the above detection accuracies, it is clear that the IAOA-BP algorithm proposed in this paper performs best in anomaly load detection.

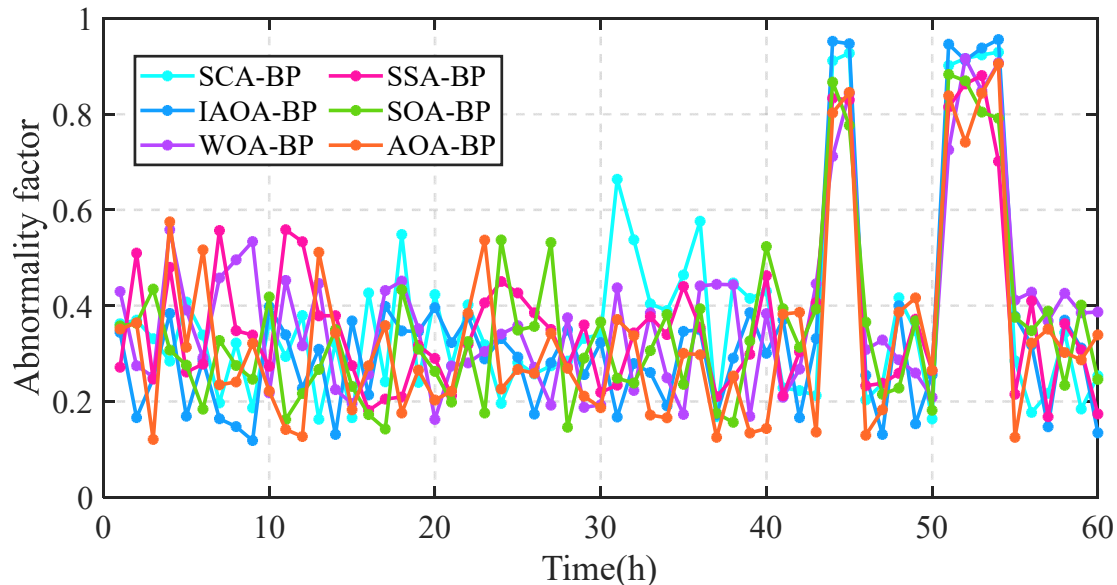


Figure 6. Graph of customer electricity consumption data anomaly factor.

In summary, we can conclude that the proposed IAOA-BP algorithm in this study has high efficiency and reliability in anomaly detection. The efficient and high detection accuracy of the IAOA-BP-based anomaly power usage detection algorithm can accurately extract the important behavioral features from the evaluation index system and add the IAOA as the weight and threshold parameter optimization algorithm to achieve more accurate and faster detection results.

5. Concluding Remarks

Traditional anomaly detection techniques are difficult to implement and are ineffective. With the aim of reducing the workload for detection and improving the effect of anomaly data detection, this study constructs an anomaly detection analysis model based on the IAOA-BP. The IAOA-BP is applied to analyze the information contained in the power consumption data and, thus, calculate the anomaly factor of the customer's electricity consumption data. On the basis of theoretical research, the effect of the electricity theft suspicion analysis is verified by data examples from a specific place, and the IAOA is found to have a higher accuracy rate compared with other algorithms, which may help to avoid the waste of human, material and financial resources in traditional anomaly detection work. Accordingly, some of the meaningful contributions of this paper can be summarized as follows.

- The IAOA algorithm with strong convergence ability and solution efficiency is proposed. For both the multi-peak and single-peak test functions, the IAOA's search results performed well compared to the comparison algorithms, indicating the effectiveness of the improvements made to the AOA in this study.
- The IAOA-BP algorithm is proposed by combining the IAOA with a BP neural network.

Anomalous data points can be quickly and efficiently identified by the IAOA-BP, which can help the electricity department to effectively flag anomalous users to further determine the cause of the anomaly.

- Compared to other algorithms, the proposed IAOA-BP algorithm has higher anomaly detection accuracy. The simulation results demonstrate that the overall determination accuracy using the IAOA-BP algorithm remains above 96%.

Some of the original contributions of this study can be summarized as follows. (1) An IAOA with superior solving power and stability is proposed. (2) An IAOA-BP algorithm is proposed. (3) The proposed IAOA-BP anomaly detection method maintains a high accuracy rate. Although the proposed power load anomaly data detection method in this study is able to check the anomalous data in the historical load data more accurately, the actual detection may lead to the reduction of the anomaly data detection speed due to the IAOA's ability to optimize the thresholds and weights of the BP neural network. Future research will focus on two points: (1) to improve the optimization capability and stability of the algorithm; (2) to further investigate how to improve the efficiency and accuracy of anomaly data detection, resulting in reduced anomaly data detection time and more accurate detection rates.

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