

Retraction

Retracted: Low-Carbon Awareness Information Technology of Enterprise Executives Based on Big Data and Multimodal Information Fusion

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] G. Yang, "Low-Carbon Awareness Information Technology of Enterprise Executives Based on Big Data and Multimodal Information Fusion," *Mobile Information Systems*, vol. 2022, Article ID 1534440, 13 pages, 2022.

Research Article

Low-Carbon Awareness Information Technology of Enterprise Executives Based on Big Data and Multimodal Information Fusion

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The so-called multimodal information refers to the information from different information sources on different or the same side of the same description target. These pieces of information are different in terms of storage structure, representation, semantic connotation, credibility, and emphasis, but there is a certain inevitable connection between them. This paper aims to study how to analyze and study the low carbon of enterprises with the help of multimodal information fusion based on the background of big data and construct the evolutionary neural network of the improved adaptive genetic algorithm. This paper puts forward the problem of low carbon in enterprises, which is based on multimodal information fusion, and then elaborates on the concept and related algorithms of multimodal information fusion. Information fusion has carried out case design and analysis. Through the research and analysis of enterprise low carbon and self-adaptive algorithm, it can be obtained that the neural network has reached the threshold of 3.95 after iterating for nearly 60 generations, and stopped iterating to obtain the best individual. The evolutionary neural network in this paper reaches stability after a small number of iterations and can basically achieve a certain low carbonization.

1. Introduction

Since human society entered the 21st century, the depletion of natural resources, air and water pollution, and global warming have caused huge damage to the global ecological environment. Under the constraints of strict environmental code of conduct, the environmental cost of enterprises is increasing, and the environmental risks are increasing day by day. Countries around the world urgently need to coordinate the harmonious development of humans and nature under the guidance of the scientific outlook on development and sustainable development, and need to establish a low-carbon economic growth model. In the background of a low-carbon economy, standardizing enterprise cost accounting requires to be innovated in all aspects. It requires that when formulating and developing low-carbon economic policies and strategies, people must always understand their basic content, optimize the economic structure, and ultimately

achieve the strategic goal of low-carbon economic development. Therefore, it is particularly important to study the low-carbon development of enterprises with multimodal information fusion.

Through the experimental process of the multimodal information fusion experiment of evolutionary neural network based on adaptive genetic algorithm, it is concluded that compared with the traditional RNFN algorithm, this paper has better training speed and efficiency, and the network can converge faster and achieve the goal. The innovations of this paper are as follows: (1) this paper combines multimodal information fusion with enterprise low carbon and introduces the theory and related methods of multimodal information fusion in detail. (2) In the face of the data set produced by the enterprise, the rough neuro-fuzzy network is compared with the multimodal information fusion algorithm and the hybrid multimodal information fusion algorithm of the adaptive genetic algorithm and neural network proposed in this paper.

2. Related Work

Low-carbon economy is an important model for implementing circular economy and sustainable energy development. Liu et al. [1] started from the system of the impact of corporate financial environment on financial accounting under the background of low-carbon economy, established a corresponding evaluation system, and studied the impact of corporate financial environment on financial accounting from the perspective of low-carbon economy [1]. Wu et al. [2] proposed the evolutionary game of low-carbon strategy between government and enterprises under the background of complex network [2]. Zhang et al. [3] developed carbon resource of the executives' pointers, including carbon reserve turnover rate, fossil fuel byproduct rate, carbon turnover rate, carbon innovation transformation effectiveness, and fixed carbon resource benefit [3]. Hillman et al. [4] analyzed the worth of social undertaking as a driver of low-carbon progress at the local area level, with an attention on the energy area [4]. Ma et al. [5] analyzed the characteristics of disruptive innovation and continuous innovation and their relationship with green manufacturing from the perspective of dynamic competitive advantage of an independent research and development enterprise in the context of green manufacturing. However, the low-carbon environmental protection awareness of enterprises has not been well implemented.

The information fusion method is the basis for the construction of the subject knowledge field. The multimodal information fusion mainly involves the feature layer and its fusion decision layer. Zhang [6] proposed a cross-modal speech text retrieval method using an interactively learned convolutional autoencoder (CAE) [6]. Nie et al. [7] introduced MMFN, a novel multimodal combination network for 3D shape acknowledgment that takes advantage of the connection among various modalities to create more powerful combination descriptors [7]. Zhao et al. [8] introduced a multimodal fusion method for generating descriptions to explain image content [8]. Domingues et al. [9] explored the important topic of multimodal data fusion in the current medical context [9]. These algorithms integrate the data to a certain extent, but the operation is more complicated and the accuracy needs to be improved.

3. Multimodal Information Fusion Method Based on Improved Algorithm

3.1. Enterprise Low-Carbon Awareness

3.1.1. Low-Carbon Manufacturing Concept. “Low-carbon manufacturing” is a brand-new concept, its meaning and significance are still in the exploratory stage, and there is no effective definition at home and abroad. In this paper, combined with research in related fields, it is defined as follows:

(1) Low-Carbon Manufacturing (LCM)

“Low-carbon fabricating” is an assembling model described by low energy utilization, low

contamination, and low fossil fuel byproducts, through low-carbon innovation, low-carbon executives, low-carbon administrations, and different means to limit ozone-depleting substance (GHG) discharges in the whole life pattern of items from configuration, producing, bundling, transportation, and use to end-of-life removal to realize economic and social development and ecological and environmental protection.

(2) The difference between low-carbon manufacturing and green manufacturing

The research related to low-carbon manufacturing is green manufacturing, and there are some differences in concept and application between the two. Literally, the difference between the two is “low-carbon” and “green.” For a clearer understanding, a brief introduction to “low carbon” and “green” is given first. It can be understood broadly that “low carbon” refers to lower greenhouse gas (CO₂-based) emissions and “green” refers to all positive impacts on the environment and safety, including impacts on global warming, eutrophication, acidification, photochemical ozone synthesis, and other factors [10, 11]. “Manufacturing” is a general term for a series of related activities and operations in the manufacturing industry, including product design, material selection, production planning, production process, quality assurance, business management, and marketing. Therefore, it is believed that “low-carbon manufacturing” is more targeted and evaluable than “green manufacturing,” focusing on reducing greenhouse gas emissions and preventing global warming more effectively. “Low-carbon manufacturing” is an important part of “green manufacturing.”

3.1.2. Architecture of Low-Carbon Manufacturing. Low-carbon production technologies include the entire life cycle of a product, especially considering resource consumption and carbon emissions, as well as technical and economic factors to coordinate and optimize the economic and social benefits of enterprises. The architecture is shown in Figure 1.

3.1.3. Key Technologies of Enterprise Low-Carbon Manufacturing Information Services. Enterprise low-carbon manufacturing information services mainly include the following key technologies:

- (1) Enterprise low-carbon manufacturing knowledge service technology includes knowledge co-construction, knowledge ordering, cognitive navigation, patent analysis, and so on. It supports enterprise employees to effectively utilize low-carbon manufacturing knowledge and realize low-carbon manufacturing.
- (2) Enterprise low-carbon manufacturing evaluation service technology includes low-carbon standard

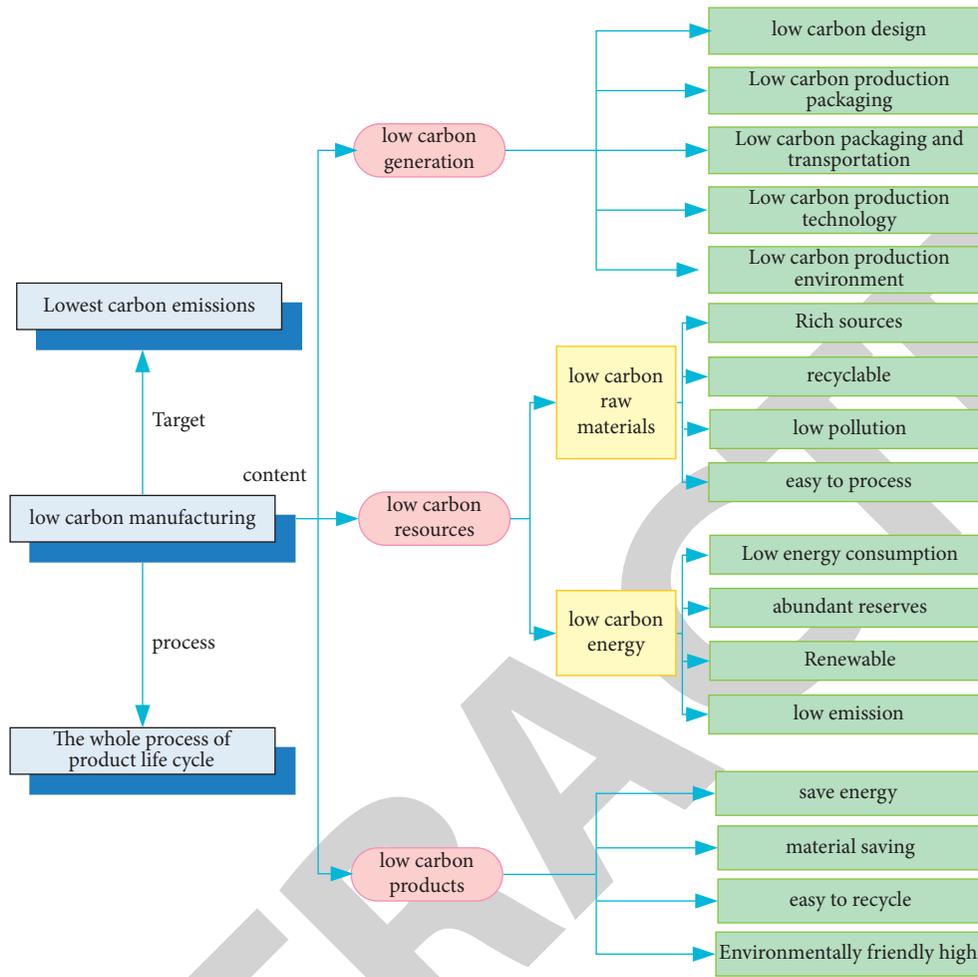


FIGURE 1: Architecture of low-carbon manufacturing.

collaborative construction, design scheme evaluation, product carbon footprint calculation, product life cycle carbon emission analysis, and so on. It helps enterprise employees understand the carbon emissions in products and manufacturing processes to take targeted measures to promote low-carbon manufacturing [12, 13].

- (3) The enterprise low-carbon manufacturing life cycle management technology includes energy consumption analysis, resource consumption analysis, pollution analysis of the whole production process of the enterprise, and so on. It helps enterprise employees collect data in the product life cycle process in a timely and accurate manner, and provides a data foundation for low-carbon manufacturing.
- (4) Enterprise low-carbon manufacturing information service unit technology aims at the garment industry. It includes clothing modular design technology for low-carbon manufacturing, clothing process optimization technology for low-carbon manufacturing, clothing production management technology for low-carbon manufacturing, clothing sales management technology for low-carbon manufacturing, and

so on. It helps corporate employees implement low-carbon manufacturing into production management and sales.

- (5) Design technology for low-carbon manufacturing plays a vital role in the implementation of low-carbon manufacturing in enterprises. It mainly helps employees to design products based on the concepts and methods of low-carbon manufacturing [14, 15].

3.2. Big Data

3.2.1. The Basic Definition and Basic Characteristics of Big Data. As far as the concept of big data is concerned, it is difficult to have a very quantitative definition. Existing definition is qualitative description from the perspective of data scale, supporting software processing capabilities. For example, Wikipedia’s qualitative description is big data that refers to unobtainable datasets, managed, and processed within a certain period of time using traditional and commonly used software techniques and tools.

Compared with traditionally processed small data, big data has the “5 Vs” characteristics, as shown in Figure 2.

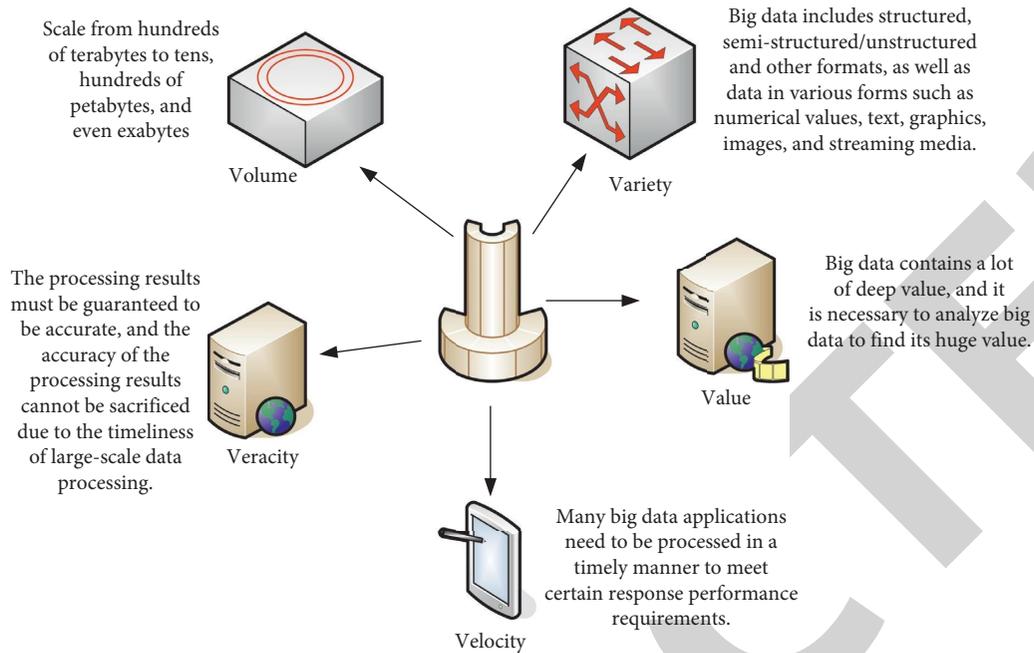


FIGURE 2: Big data “5V” characteristics.

3.2.2. Big Data Processing Technology Stack and Its Processing Framework. Enormous information is the combination of numerous PC advancements at various levels, and huge information handling is an exhaustive data handling innovation, including all levels of the whole programming and equipment framework. A total large information handling framework is a bunch of advances, including huge information stockpiling, PC, examination, and other specialized viewpoints. Therefore, the processing of big data has strong technical integrity and intersectionality. From base to top, the whole innovation stack fundamentally incorporates foundation and asset levels, huge information framework programming layer (counting circulated capacity and equal PCs), investigation calculation layer, and large information application layer [16, 17].

Table 1 describes the main technical aspects and technical contents of the big data processing technology stack. Each layer in the technology stack has its own functions and features.

3.2.3. Big Data Parallel Computing Technology and System. The big data parallel computing system is the computing core layer in the whole big data processing process. Hadoop MapReduce was almost the only platform for processing big data in the early years. With the popularity of big data applications, people realize that the big data processing requirements in practical applications are complex and diverse, and it is difficult to have a single computing model that can cover different big data computing characteristics. Table 2 summarizes common big data computing patterns and their typical systems.

3.3. Multimodal Information Fusion

3.3.1. Research on Information Fusion Methods. In past research, information fusion methods can be mainly divided into three categories. The rule-based information fusion method, the classification-based information fusion method, and the estimation-based information fusion method together constitute the basic methods of information fusion at different levels, as shown in Table 3.

3.3.2. Multimodal Information Fusion Model Based on Brain Cognition. The perception of the intelligent subject to the outside world or its own state can be abstracted into the human body’s perception of the response to external stimuli and changes in its own state. Figure 3 shows the information fusion model based on brain cognition. Human organs such as eyes, ears, and nose are like various sensors for intelligent agents. Through them, complex multimodal information is obtained and fused through the cognitive mechanism of the brain, combined with the prior domain knowledge base, to form perception, judgment, and reasoning and decision-making for the target. Intelligent agents can also rely on multisensor and intelligent information fusion models to achieve the same purpose [18, 19].

3.3.3. Functional Model of Multimodal Information Fusion. The functional model of multimodal information fusion includes various functional modules. According to the level of information in the transmission process, it is divided into low-level processing and advanced processing, as shown in Figure 4.

TABLE 1: Big data processing technology stack.

Big data application layer	Application and administration layer in the field of large information	Transportation/Telecom/Medical/Finance/Public Security/Business/Biology/Remote Sensing/Mineral Exploration. . . Domain application/service requirements and analysis model
	Application design and development layer	Huge information application improvement climate and device stage
Big data analysis algorithm layer	Comprehensive analysis algorithm layer	Informal organization examination, picture handling, regular language handling, biological information processing, media analysis and retrieval, Web information mining and retrieval, visual computing, etc.
	Basic algorithm layer	Parallelized basic analysis algorithms
Big data computing layer	Parallel computing system platform	General equal registering framework Hadoop, Spark, diagram processing framework GraphLab, stream figuring framework Storm, and so forth.
	Parallel computing mode	Clump handling, streaming processing, chart registering, iterative figuring, inquiry examination, memory computing, and other computing modes
Big data storage layer	Distributed database	Distributed database storage system
	Distributed file system	Distributed file storage systems
Big data processing resource layer	System architecture and hardware resources	Deeply, half breed heterogeneous stage distributed computing assets and backing stage

TABLE 2: Typical big data computing modes and systems.

Big data computing model	Typical systems and platforms
Iterative calculation	Apache Spark, HaLoop, iMapReduce, Twister, etc.
In-memory computing	Dremel, Apache Spark, Apache Flink, etc.
Streaming computing	Storm, Apache Spark Streaming, s4, etc.
Batch computing	Apache Hadoop MapReduce, Apache Spark, etc.
Graph computation	Pregel, Giraph, GraphLab, GraphX, etc.
Big data query analysis and calculation	Apache Hive, Impala, Apache Spark SQL, Apache Kylin, etc.

TABLE 3: Introduction of different types of information fusion methods.

Method	Introduce
Classification-based fusion methods	Support vector machines, Bayesian inference, DS evidence theory, dynamic Bayesian networks, neural networks, and maximum directed models
Estimation-based fusion methods	Kalman filter, extended Kalman filter, and particle filter
Rule-based fusion methods	Linear weighted fusion, majority voting rules, and custom rules

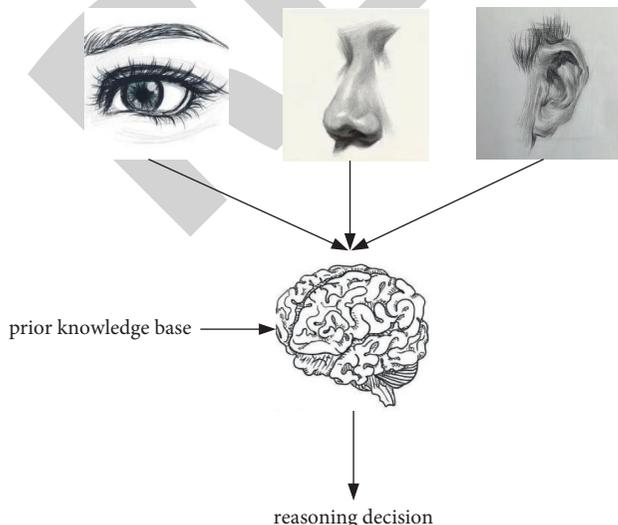


FIGURE 3: Information fusion model based on brain cognition.

In the early stage of the low-level processing process, numerical results are formed by mining the characteristics of the information data. These results can reflect the basic signal signs of multimodal information and can realize the correlation and identification between data. The advanced processing process is analyzed in the later stage of information fusion and reflects the characteristics of the semantic level. It mainly extracts information features for symbolic logic and can realize functional modules such as logical reasoning and situation estimation.

3.3.4. *Analytic Hierarchy Process of Multimodal Information Fusion.* The process of signal information processing is information data processing [20, 21], and the level of information fusion is shown in Figure 5.

Data layer fusion is the first layer of fusion. The system directly merges data after using multiple sensors to collect raw data, which is characterized by less information loss and

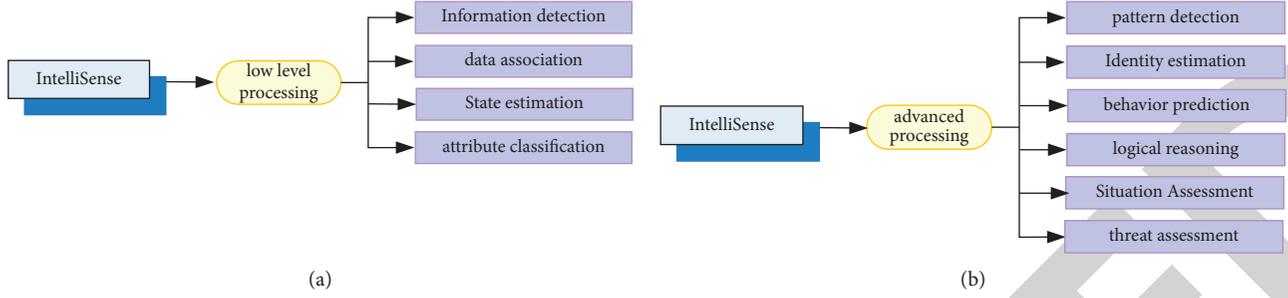


FIGURE 4: Multimodal information fusion functional model. (a) Low-level processing. (b) Advanced processing.

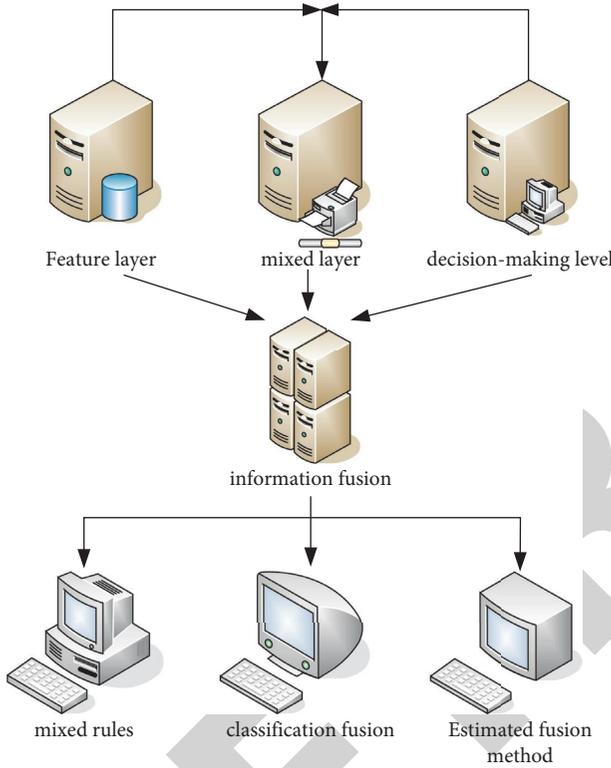


FIGURE 5: Information fusion methods based on different layers.

more accurate fusion results. However, due to the complex and noisy data collected, and the large amount of fusion calculation, the sensor types must be consistent, and the information synchronization requirements are relatively high. The feature layer is merged into the second layer. After data processing, the information expressed by the data is purer. Therefore, the information can be extracted by features, and the obtained feature vectors can be uniformly processed to judge. This fusion method requires relatively little computation and does not require high sensor types and synchronization, but the fusion results are greatly affected by feature information and are susceptible to interference [22, 23].

The moment of fusion processing at the decision-making level is that the system has formed the preliminary detection results of the target, but these results are the judgment of the sensor on the single-source signal, which is one-sided. At

this time, the decision-level fusion processing can make the system fuse the single-source detection results to form a more complete and accurate judgment. This method requires the least amount of calculation and has the strongest anti-interference ability. However, due to the difficulty of obtaining prior knowledge and the difficulty of constructing a huge knowledge base, the related theories need to be further improved.

3.3.5. Commonly Used Multiphysical Domain Multimodal Information Fusion Methods and Their Characteristics. As a branch of signal processing, there have been many research achievements in information fusion. From the perspective of the integrated functional model, it can be divided into three aspects: correlation, estimation, and identification. The specific processing methods and the characteristics of some methods are shown in Table 4.

3.4. Multimodal Information Fusion Algorithm Based on Improved Adaptive Genetic Algorithm and Neural Network Hybrid

3.4.1. Genetic Algorithm. In standard genetic algorithms, selection criteria are based on the principle of proportionality. Therefore, through the action of the a th selector, the expected value of the number of people who will continue to exist in the next generation is $m(f_a/\sum f)$, and then, there is

$$\bar{f}(K, e) = \frac{1}{m(K, e)} \sum f_a. \quad (1)$$

So,

$$m(K, e + 1) = m(K, e) \cdot \bar{f} \frac{(K, e)}{f(e)}. \quad (2)$$

The equation shows that the effect of the selection operator will increase (decrease) the ability of a pattern above (below) the average to be applied across generations, and improve quality.

Then, the effect of the crossover operator is analyzed. This plan can obviously be maintained in the next generation if there is no intersection or if the intersection point is beyond the character positions specified on the left and right ends of the figure. Therefore, the probability W_s that the K mode continues to exist in the next generation should satisfy

TABLE 4: Fusion methods and their characteristics.

Fusion method	Specific description	Advantage	Shortcoming
Neural networks	Perform forward calculation and reverse parameter adjustment on labeled data to construct a model with appropriate weights and biases.	In theory, it can fit any complex function and has strong generalization ability.	The amount of calculation is large, and the parameter adjustment process depends on human experience.
D-S evidence theory	The generalization of Bayesian estimation, introducing the trust function, and the likelihood function to obtain the basic probability distribution function.	The required prior knowledge is more intuitive and easier to obtain than that in Bayesian estimation, and the knowledge and data of different experts or data sources can be integrated, and the description of uncertain problems is very flexible and convenient.	Evidence needs to be independent. The theory of evidence synthesis has no solid theoretical basis, and there is a potential exponential explosion in calculation.
Kalman filter	Utilizing the straight framework state condition, through the framework information and result perception information, the ideal assessment calculation of the framework state.	Using original data for fusion, less information loss.	The equation of state is difficult to establish and solve, and its scope of application is limited.
Weighted average method	A number of observations of the same variable arranged in time order are weighted by the time order number, and the weighted arithmetic mean of the observations is calculated.	The model is simple, and less information is lost.	The weights have a great influence on the fusion results and are not easy to determine.
Bayesian estimation	Utilize Bayes' hypothesis to consolidate new proof with past earlier probabilities to get new probabilities.	There are specific mathematical models, which are easily accepted.	Certain prior knowledge needs to be obtained, and the prior knowledge has subjective differences, which affects the posterior results.

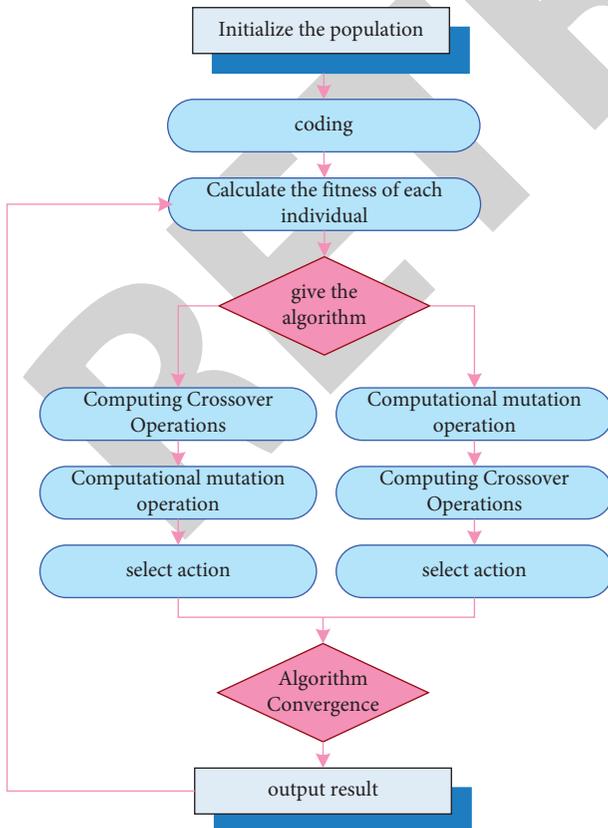


FIGURE 6: Adaptive genetic algorithm solution process.

$$W_s \geq 1 - W_c \cdot \varphi \frac{(K)}{(L-1)}. \quad (3)$$

Taking into account the effects of selection and crossover, there is

$$m(K, e+1) \geq m(K, e) \cdot \bar{f}(K, e) \cdot \frac{[1 - W_c \cdot \varphi(K)]}{(L-1) \bar{f}(e)}. \quad (4)$$

Under the action of the mutation operator, the probability that K continues to exist is

$$(1 - W_n)^{O(W)} \approx 1 - W_n \cdot O(W). \quad (5)$$

The probability of unreserved is about $O(K) \cdot W_n$. Therefore, considering the functions of selection, crossover, and mutation operators, this equation can be finally gotten

$$m(K, e+1) \geq \frac{m(K, e) \cdot \bar{f}(K, e) \cdot [1 - W_c \cdot (\varphi(K)/L - 1) \cdot W_n]}{\bar{f}(t)}. \quad (6)$$

Specifically, if $\bar{f}(K, e) = f(e)(1+c)$, $c > 0$ and it is constant, then

$$m(K, e) = m(K, e-1)(1+c) = m(K, 0)(1+c)^e. \quad (7)$$

3.4.2. Improved Algorithm Design and Method. The improvement is applied to the traditional genetic algorithm, and the execution flow is shown in Figure 6.

Combining evolutionary algorithms with neural networks is a great way to complement each other's strengths.

There are usually two forms of genetic algorithm optimization neural network: auxiliary and cooperative. The advantages of the genetic evolution neural network in the field of deep learning that it can adaptively learn evolution make it more and more applications and research, but there are many issues to be considered for specific implementation:

(1) *Encoding Method*. In recent years, due to the high complexity of practical problems, many improvements have been made to the traditional binary coding method of genetic algorithms. These include the real number encoding method that improves the solution accuracy, the permutation encoding method [81] that performs well in combinatorial optimization problems, the matrix encoding method that can transmit multidimensional information, and so on.

$$F(z) = -f(z),$$

$$F(z) = \begin{cases} D_{\max} - f(z), & f(z) < D_{\max}, \\ 0, & \text{others,} \end{cases} \quad F(z) = \frac{1}{1 + d + f(z)}, \quad d \geq 0, d + f(z) \geq 0. \quad (9)$$

D_{\max} is the maximum estimate of $f(z)$, and d is a conservative estimate of the bounds of the objective function.

(2) *Fitness Calculation*. In hereditary calculation, the size of wellness addresses the benefits and detriments of people in natural development. It figures out which top notch people can develop into the future and which substandard people should be wiped out.

The basic expression equation of fitness function is as follows:

$$F(z) = gf(z). \quad (8)$$

f is the objective function, the moment when g is positive or negative depends on $f(z)$, and F is the relative fitness of the population.

If the objective function is a minimization problem, then

If the objective function is a maximization problem, then

$$F(z) = -f(z),$$

$$F(z) = \begin{cases} f(z) - D_{\max}, & f(z) > D_{\max}, \\ 0, & \text{others,} \end{cases} \quad F(z) = \frac{1}{1 + d - f(z)}, \quad d \geq 0, d - f(z) \geq 0. \quad (10)$$

D_{\max} is the maximum estimate of $f(z)$, and d is a conservative estimate of the bounds of the objective function.

For the likelihood of individual selection, there are two widely used allocation methods: proportional fitness allocation and classification-based.

(1) *Proportional Fitness Allocation Method*. Proportional allocation must satisfy that f_{avg} does not change before and after transformation, and the maximum value of $f(z_a)$ after transformation should be equal to the multiple of f_{avg} before transformation. It can ensure that the number of individual copies remains unchanged and can control the individual with the greatest fitness not to replicate in large numbers, preserving the diversity of the population. At this time,

$$F(z_a) = mf(z_a) + n, \quad (11)$$

where $f(z_a)$ is the fitness of the individual z_a , m is the scalar coefficient, n is the offset value, and $F(z_a)$ is the fitness value generated by the individual.

$$f_{\min} > \frac{\text{Smul} \times f_{\text{avg}} - f_{\max}}{\text{Smul} - 1.0}. \quad (12)$$

Usually, the range is [1.0, 2.0], and the coefficient of the linear scale can be obtained according to the preconditions

$$m = \frac{(\text{Smul} - 1.0)}{f_{\max} - f_{\text{avg}}} f_{\text{avg}},$$

$$n = \frac{f_{\max} - \text{Smul} - 1.0}{f_{\max} - f_{\text{avg}}} f_{\text{avg}}. \quad (13)$$

Otherwise,

$$m = \frac{f_{\text{avg}}}{f_{\text{avg}} - f_{\min}},$$

$$n = \frac{-f_{\min} \times f_{\text{avg}}}{f_{\text{avg}} - f_{\min}}. \quad (14)$$

Smul is a user-specified multiple, and f_{avg} is the average among the current offspring.

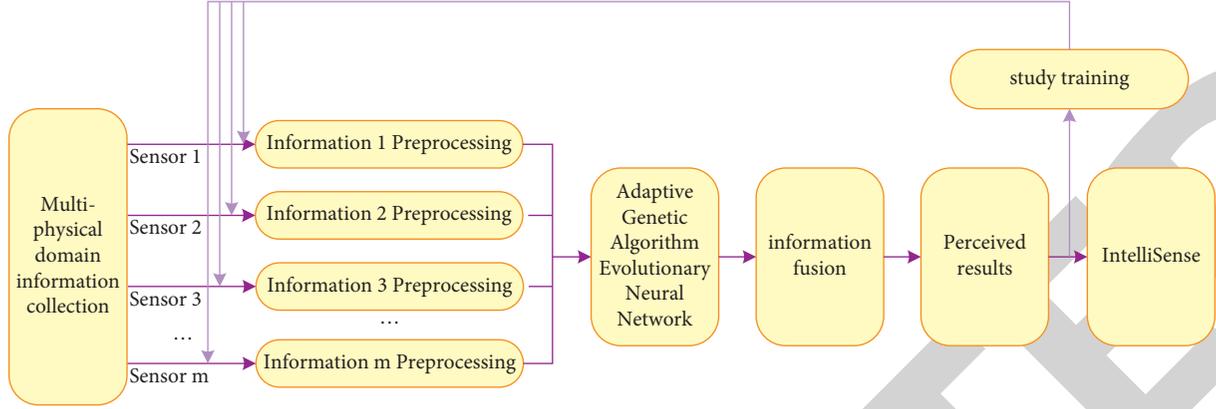


FIGURE 7: Multiphysical domain information fusion model process.

(2) *Rank-Based Fitness Assignment Method*. This method can limit the living range of offspring and calculate the fitness according to the order of individuals in the population, which can prevent individuals from producing extreme offspring, and restrains premature convergence to a certain extent.

For linear sorting, the fitness value is calculated as follows:

$$\text{FitnV}(\text{Pos}) = 2 - sp + \frac{2 + (sp - 1)(\text{Pos} - 1)}{W_{\text{ind}} - 1}, \quad sp \in [1.0, 2.0]. \quad (15)$$

The number of individuals in the population is denoted as W_{ind} , and the difference in selection pressure is denoted as sp , which determines the displacement or force of selection.

For nonlinear sorting, the fitness value calculation equation is as follows:

$$\text{FitnV}(\text{Pos}) = \frac{W_{\text{ind}} \times Z^{\text{pos}-1}}{\sum_{a=1}^{W_{\text{ind}}} Z^{a-1}}. \quad (16)$$

Z is the absolute value of the roots of the polynomial equation

$$(sp - B_{\text{ind}})Z^{B_{\text{ind}}-1} + spZ^{B_{\text{ind}}-2} + \dots + spZ + sp = 0. \quad (17)$$

(3) *Parameter Setting*. Boundaries characterized in transformative calculations incorporate chromosome length, populace size, hybridization likelihood, change likelihood, number of redundancies, and organization levels. Every boundary will influence the exhibition of the calculation. As of now, analysts have done a great deal of exploration on the determination and streamlining of transformative calculation boundaries. The selection of boundaries straightforwardly influences the redundancy pace of the calculation and the precision of the arrangement. The hybridization likelihood, which influences the general flexibility, and the change likelihood, which decides the adequacy of the neighborhood search, are the two most significant boundaries.

4. Multimodal Information Fusion Experiment of Evolutionary Neural Network Based on Adaptive Genetic Algorithm

4.1. Multiphysical Domain Information Fusion Model Process.

The process of multiphysical domain information fusion of intelligent agents is shown in Figure 7, and the specific process is as follows:

- (1) The handling object is furnished with different designated sensors, and the securing framework is utilized to acquire the applicable data of the article and get multistation signal information.
- (2) The gained data are turbulent and uproarious, which cannot be straightforwardly melded. The sign should be mined and the commotion eliminated.
- (3) Multi-actual space data highlight layer combination. The sign highlights acquired from (2) are taken as information, and the data combination model in view of brain network is utilized to incorporate the multimodular sign elements and get the combination results.

4.2. Data in the Production Process of the Enterprise

4.2.1. *Neural Network Simulation and Result Analysis*. To confirm the possibility of the versatile hereditary calculation brain organization, the python language is utilized for programming considering the PyCharm stage, and the perfect python module is utilized to build a versatile brain organization, which is utilized to pass judgment on the exemplary XOR issue. The XOR problem is a modified version of the OR problem, and its rules are as follows:

- (1) Input true, true, output false;
- (2) Input false, true, output true;
- (3) Input true, false, output true;
- (4) Input false, false, output false.

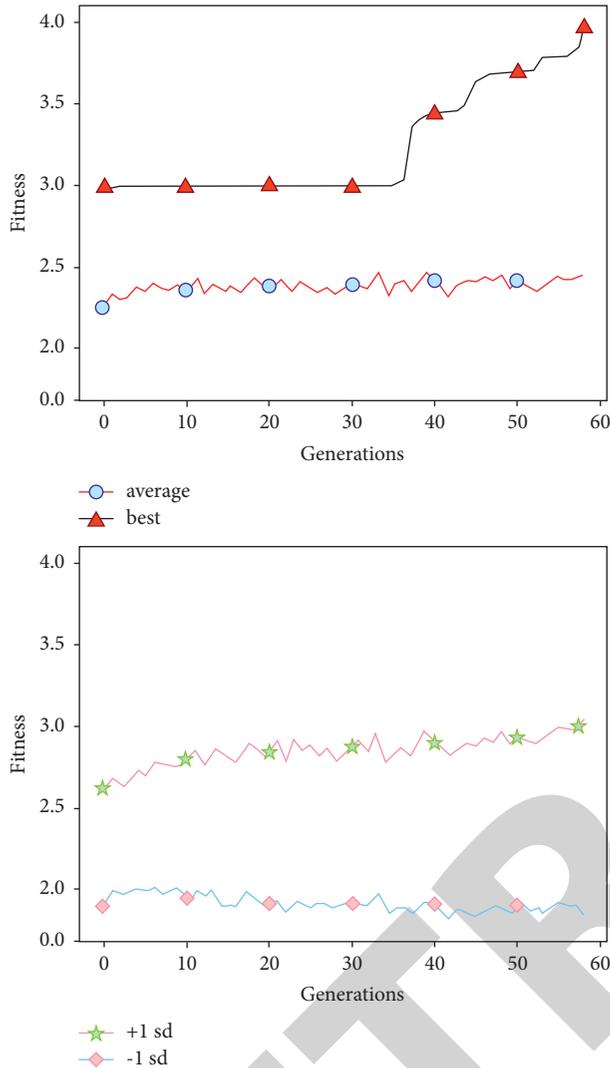


FIGURE 8: Population fitness curve based on neural network.

Figure 8 shows the population average and highest fitness change curves. The fitness of the neural network reaches the threshold of 3.95 after iterating for nearly 60 generations, and the iteration is stopped to obtain the best individual.

4.2.2. Simulation Results and Analysis. In order to verify the feasibility of the multimodal information fusion method based on the evolutionary neural network of adaptive genetic algorithm, this paper conducts algorithm simulation through the low-carbon production experiment of enterprises, which is a typical intelligent low-carbon experiment.

The network sets the initial hidden layer to be 0, which allows the neural network to evolve from the simplest structure and achieve the purpose of light weight, which is also the advantage of the evolutionary neural network. The population size (`pop_size`) is set as 100, and two outputs are set as left and right offsets, respectively. Relu is used in the activation function, so that the function has nonlinear fitting ability. The fraction of each production energy consumption is used as individual fitness, and the fitness threshold of

offspring is set as 1. After the network is created and evaluated, a neural network can be generated for each individual, and each neural network can be tested for production energy consumption. In one iteration, the network will test the network of each individual for 10 rounds and finally select the round with the least reward among all rounds of an individual as the fitness of the network. When any fitness reaches 1 or the number of iterations reaches 300 times, iterating and updating the population will stop, and output the winner neural network is used to predict. Figure 9 selects the average and highest fitness change curve of the population in the three experiments. It can be seen that there are children in the neural network population that quickly reach the fitness threshold, and stop the iteration to obtain the best individual.

It can be seen from the results that for an enterprise's low-carbon information analysis technology problem, the evolutionary neural network achieves stability after a small number of iterations and can basically achieve a certain low carbonization. The network structure generated by the evolutionary neural network is quite simple compared to the case where the hidden layer of reinforcement learning often has dozens or hundreds of hidden nodes. The adaptive genetic algorithm neural network can generate a relatively simple network structure with fewer iterations when facing the technical problems of enterprise low-carbon information analysis, and can learn faster to achieve the goal.

The data set generated in the production process of the enterprise is trained. In order to verify the effectiveness of the algorithm, the rough neural fuzzy network is compared with the adaptive genetic algorithm and neural network hybrid multimode information fusion algorithm and neural network hybrid multimode information fusion algorithm proposed in this paper. Comparing the efficiency of the two algorithms in model training and the degree of fitting to the expected value of the enterprise's production energy consumption, the test results of the model are shown in Figure 10.

In terms of simulation performance, the network exhibits strong generalization ability and recognizes behavioral patterns, and allows the creation of inference mechanisms in various aspects without relying on human experts in high-complex systems. It can be seen from Figure 10 that the algorithm in this paper has a better fitting effect on the low-carbon production status of enterprises. Compared with the traditional RNFN algorithm, this paper has better training speed and efficiency, and the network can converge faster and achieve the goal.

4.3. Enterprise Cost Accounting in a Low-Carbon Economy.

There is a growing awareness that it is unreasonable to include all environmental costs in general production costs. While environmental costs are critical, not all costs are associated with cost centers and some can be classified as part of general overhead. Additional costs associated with the flow of materials and waste generated during production are unrelated to common cost centers and often overlooked.

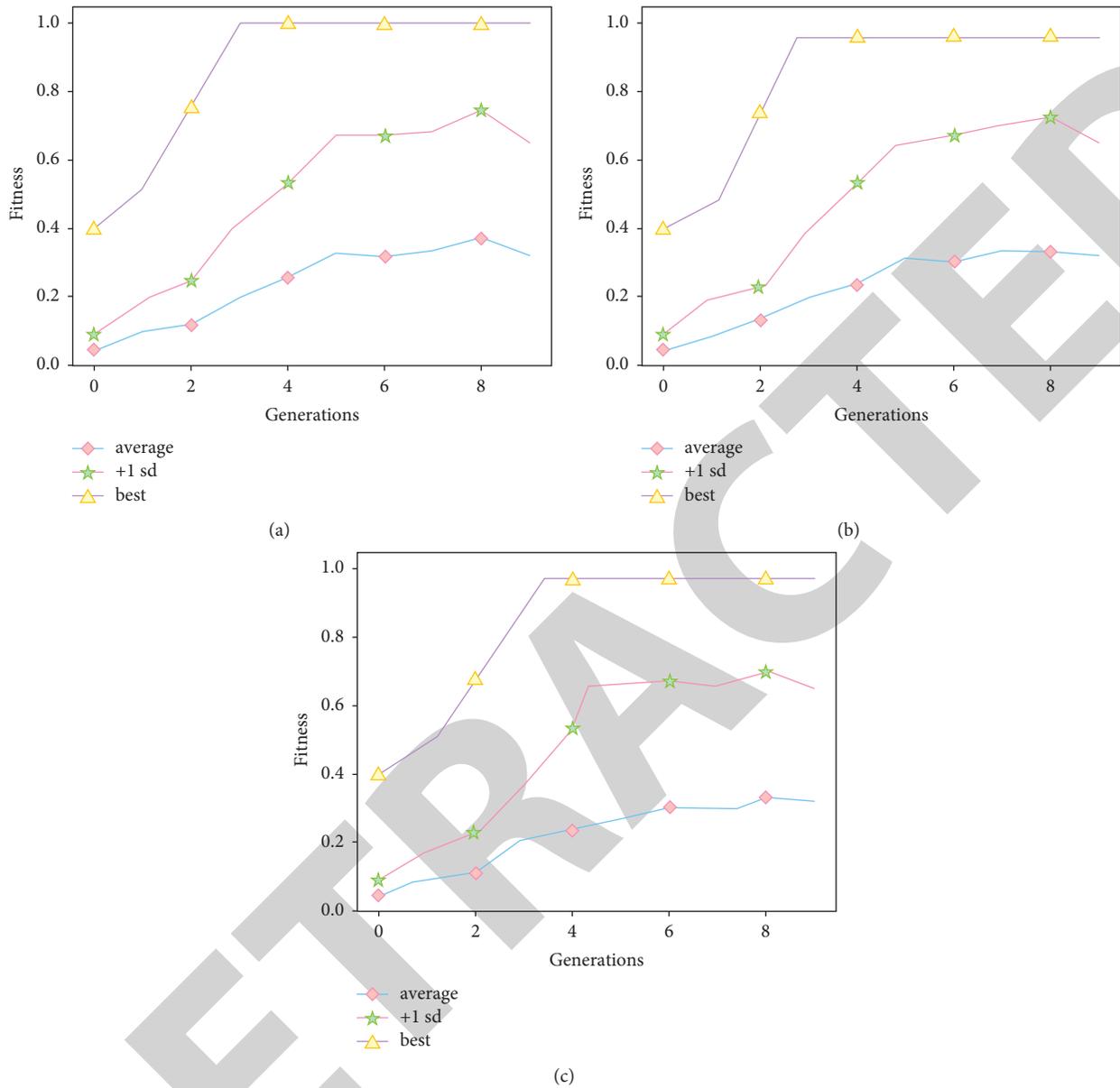


FIGURE 9: Population fitness curve. (a) The first experiment. (b) The second experiment. (c) The third experiment.

This part of the cost of this waste will inevitably be saved if waste is reduced at the source. Efficient use of resources in product production will reduce waste and improve economic efficiency.

- (1) In the production process, by introducing the cost method, the material flow and energy flow in the production and operation process of the enterprise can be monitored, and the visualization of the material flow and value flow of the enterprise can be improved. As a result, business managers can better understand material and energy waste and then take effective measures to improve congestion point procedures at each production plant.

- (2) In terms of investment decision making, the result of accounting cost can provide effective information for the enterprise's investment decision making.
- (3) In terms of resource consumption, the application of the logistics cost accounting method reduces the waste of the company's resources, thereby reducing the resource consumption in the company's production and operation activities, effectively alleviating the problem of resource shortage, and improving environmental performance.
- (4) In terms of environmental protection, for a long time, low-level manufacturing, as an important part of economic growth, will become China's leading

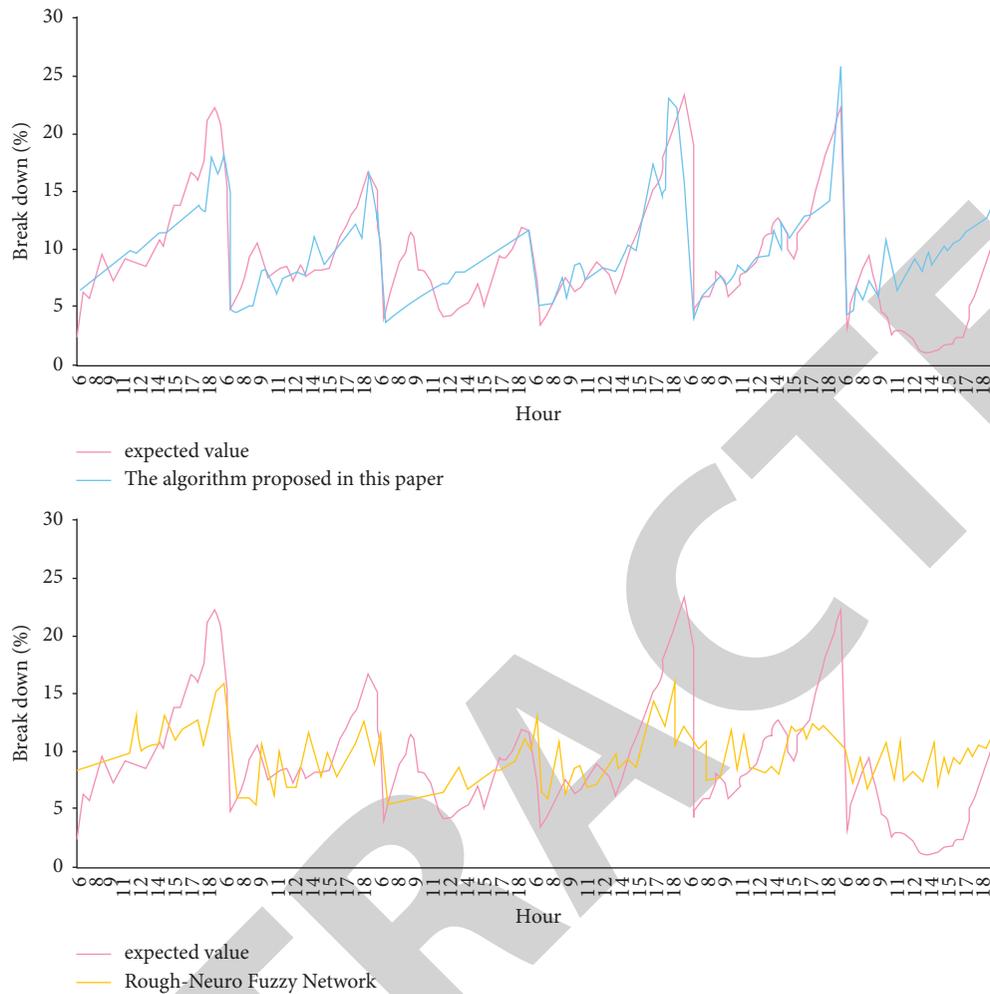


FIGURE 10: Production energy consumption forecast results.

industry and pollutants emitted by production enterprises in the production process. Using the logistics cost accounting method, the company can accurately calculate the amount of waste processed and take effective improvement measures to reduce the discharge of harmful substances and reduce the adverse impact on the environment.

5. Discussion

This paper analyzes how to conduct research on enterprise low carbon based on big data and multimodal information fusion. The concept and algorithm of multimodal information fusion are expounded, the low-carbon awareness of enterprises is studied, and the analysis hierarchy process of multimodal information fusion is explored. And through experiments, this paper analyzes the applicability of evolutionary neural network multimodal information fusion based on adaptive genetic algorithm in low-carbon production of enterprises.

Through the analysis of raw and auxiliary material consumption data and waste data, enterprises can compare the current and historical consumption of raw and auxiliary

materials in the production process of each unit of product, and analyze the utilization rate of materials and the degree of environmental pollution. Through the analysis of electricity, water, fuel, and other usage data in the production process of a batch of products, it is possible to find out the production process with high energy consumption, and take energy-saving and emission-reduction measures. Therefore, enterprises must record the input and output data of each quarter or each batch production.

The results can be seen from the experimental analysis in this paper: as one of the most important ways to raise the awareness of low-carbon enterprises, the essence of cost accounting coincides with the goals of Chinese enterprises to improve cost management, reduce material and energy consumption, save costs, and optimize the environment and economic benefits. Promoting low-carbon emissions is the most necessary accounting method for economic growth.

6. Conclusions

The study of low-carbon enterprise production is a large systematic effort, and many issues have not been investigated or covered in depth in this paper. This paper failed to give an

in-depth and detailed elaboration on the relevant theories of low-carbon production in enterprises. The research content focused on theory and lacked systematic research to support empirical research. In this huge mechanical system, there are many problems that need further study. This article is only a small part of the mechanical system. It is hoped that through this article, the research on the environmental cost management of enterprises can allow enterprises to enjoy the economic benefits of green mountains and clear waters, and realize the harmonious coexistence of humans and nature.

Data Availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Conflicts of Interest

The author declared that there are no conflicts of interest with any financial organizations regarding the material reported in this manuscript.

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