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Research Article

Application of Neural Network Based on Multisource Information Fusion in Production Cost Prediction

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Production cost forecasting is an important basis for cost accounting, cost decision-making, and cost planning. It is the scale necessary to reduce product costs and an important way to enhance enterprise competitiveness and improve system benefits. A neural network based on multisource information fusion is a manifestation of integrated internal knowledge. By learning to integrate multiple sources of information, it is easier to understand cognitive thinking and integrate the complex relationships of uncertain regions into regular signals. Fusion prediction does not need to understand the specific mechanism of the process but can fully approximate various nonlinear functional relationships determined by input and output with the continuous update of its internal weights. This paper mainly studies the application of neural network based on multisource information fusion in production cost prediction, analyzes the technology of multisource information fusion, and proposes a method of applying multisource information fusion theory to BP neural network and RBF network. Experiments have proved that through the comparison of the results of the BP neural network and the RBF network, for the six cost categories, compared with the BP neural network, the prediction results of the RBF network are closer to the true value, and they all show higher prediction capabilities. Among them, the error of the RBF network in predicting the total salary of the current month is 0.01004. The performance of the RBF network model is better than that of the BP neural network model.

1. Introduction

China is in a period of in-depth development of industrial growth, information development, urban promotion, and agricultural renewal, and product demand will see new growth. Multisource information fusion is a multilevel, multistep process, with the characteristics of availability, compatibility, and aggregation of multisource data, so as to regularly improve status and identity analysis. Due to its high availability, good scale, high reliability, and low cost of information retrieval, it has been widely used in modern military and civilian environments, promoting the development of modern technology and the improvement of human life. In recent years, multisensor information fusion technology has received extensive attention and applications. Information fusion is a new research direction of generating information, which solves the specific problem of using multiple sensors (multiple or multiple types) in the system. If an enterprise wants to obtain and maintain long-term competition, it must face the problem of insufficient production cost control to improve its system performance and competitiveness. However, in today's relatively saturated market, market prices are the decisive factor in the market, and market prices are severely restricted by market costs. Therefore, deepening corporate cost control, lowering market prices, and ensuring corporate profit growth are the keys to the survival and development of the industry. Pricing forecast is also the primary link and foundation for enterprises to achieve greater economic benefits and pursue primary goals.

Although the use of deep learning and neural network technologies is becoming more and more popular, there are still some challenges when it comes to combining multiple sources of information and data. Bayesian reasoning provides a rigorous method for the quantification of uncertainty in decision-making. The uncertainty quantification using Bayesian inference takes into account the uncertainty related to the model parameters and the uncertainty of combining multiple data sources. Chandra and Kapoor proposed a

Bayesian framework for transfer learning using neural networks, which considers single and multiple data sources. They used the existence of the prior distribution to define the dependence between different data sources in the multisource Bayesian transfer learning framework and used the Markov chain Monte Carlo method to obtain samples from the posterior distribution. The results show that the framework provides a robust probabilistic method for decision-making, but the experimental data is not clear [1]. Recently, self-centered activity recognition has attracted considerable attention in the pattern recognition and artificial intelligence community because it is widely applicable to human systems, including the evaluation of diet and physical activity, as well as the monitoring of patients and the elderly. Yu et al. proposed a knowledge-driven multisource fusion framework to identify self-centered activities (ADL) in daily life and designed a simple likelihood table to provide everyone with regular ADL information. Then, a well-trained convolutional neural network is used to generate a set of text labels, together with regular information and other sensor data, which are used to identify ADL based on statistics and support vector machines based on information theory. Experiments show that the proposed method accurately recognizes 15 predefined ADL categories, including various sedentary activities that were previously difficult to recognize. When applied to real-life data recorded using self-built wearable devices, the method is better than previous methods. The average accuracy of 15 ADLs reached 85.4%, but this research has not yet been widely used [2]. Recently, artificial neural networks (ANN) have been applied to various robotics-related research fields due to their powerful spatial feature abstraction and temporal information prediction capabilities. ANNs are connectionist models, which means that they are naturally weak in long-term planning, logical reasoning, and multistep decision-making. Zuo et al. proposed an improved ANN (SANN) model of State Calculator and Result (SOAR), which simultaneously utilizes the long-term cognitive planning capabilities of SOAR and the powerful feature detection capabilities of ANN. It imitates the cognitive mechanism of the human brain and uses an additional logical planning module to improve the traditional ANN. In addition, they also built a data fusion module to combine the probability vector obtained by SOAR planning with the original data feature array. The experimental results show the efficiency and high accuracy of the proposed architecture, and it also has great potential for more complex tasks that require robust classification, long-term planning, and fast learning. Some potential applications include recognizing the grabbing sequence in a multiobject environment and multiobject cooperative grabbing, but the practicality is not strong [3]. With the development of the Industrial Internet of Things, diagnosis based on data fusion is attractive for effective use of multisource monitoring information of motors. Following the paradigm of multimodal deep learning (MDL), Fu et al. proposed a new multisensory fusion model called multimodal neural network based on dynamic routing (DRMNN). Specifically, they studied the fusion of vibration and stator current signals and designed a multimodal feature extraction scheme for dimensionality reduction and invariant feature capture based on multisource information. Since it is necessary to determine the importance of each mode, a dynamic routing algorithm is introduced in the decision-making layer to adaptively assign appropriate weights to different modes. The effectiveness and robustness of the developed DRMNN have been proven in an experimental study conducted on a motor test platform. However, the experimental subjects are somewhat one-sided and cannot be used in real life [4]. In order to solve the problem of complicated robot assembly and learning process and high requirements for programming technology, Wang et al. proposed an implicit interaction method based on forearm sEMG (surface electromyography) and inertial multisource information fusion to realize robot demonstration programming. Based on the assembly experience gained by the demonstrator's demonstration and learning, they proposed a multiple depth deterministic strategy gradient (M-DDPG) algorithm to modify assembly parameters to improve the adaptability to assembly objects and environmental changes. In the demonstration programming experiment, they proposed an improved PCNN (Parallel Convolutional Neural Network), namely, one-dimensional PCNN (1 D-PCNN); the feature inertia and EMG are automatically extracted through one-dimensional convolution and pooling, which improves the generalization performance and accuracy of gesture recognition to a certain extent, but the experimental operation is too complicated [5]. Previous literature has shown that the prior sharing of imperfect demand information by retailers will harm retailers, benefit manufacturers, and reduce the total profit of the supply chain. Zhao and Li extend the research of information sharing to include that manufacturers may have the ability to invade and may face uneconomical or economic production. When the manufacturer's production costs are not considered, the expropriation of manufacturers encourages retailers to share demand information with manufacturers and improve supply chain performance. In addition, manufacturers may have incentives to encourage retailers to improve the accuracy of demand forecasts. When the manufacturer infringes and faces production diseconomy, information sharing is beneficial to the retailer, and it is beneficial to the manufacturer and the supply chain when the production diseconomy is relatively small. When the demand becomes more volatile or the retailer's demand signal becomes more accurate, the retailer will get more benefits from the following aspects, but the specific quantitative relationship has not been studied in depth [6]. An educational publishing industry usually builds up large inventories for "on-demand production"; however, frequent revisions can lead to obsolescence problems. Lee and Liang proposed two models to solve different but related problems, inventory scrap, and contract design. The industry uses predictive models to forecast demand and manage inventory of various printed products. This model was developed to improve the accuracy of demand forecasts and reduce inventory obsolescence. In addition, there is information asymmetry in a two-side supply chain, and contract design is conducive to educational publishing retailers. Therefore, the profit margin of the entire supply chain has not been maximized, and the manufacturer's profit is also very limited. The research suggests encouraging retailers to provide real information to improve the profitability of the entire supply chain. An empirical study of leading education publishers in Taiwan validated the proposed model. The results show that the proposed printing decision model improves the prediction accuracy by 3.7% and reduces the cost by 8.3%. The contract design improves the profitability of the overall supply chain and the manufacturer by 0.5% and 2.7%, respectively, but the initial capital investment is too large [7]. The above research makes a detailed analysis on the application of neural network and multisource information fusion. It is undeniable that these studies have greatly promoted the development of corresponding fields. We can learn a lot from methods and data analysis. However, there is relatively little research on the prediction of production cost in the field of neural network. It is necessary to fully apply these algorithms to the research in this field. This paper combines neural network and information fusion system and proposes two information fusion algorithms based on neural network. Combining the advantages of multisource signals and neural networks, embed the multisource information processing mechanism into the neural network. Through the learning of BP neural network and RBF network, the ability of neural network to process information is broadened, and it proves the superiority of multisource information fusion compared with single information fusion. After training, the neural network does not need any additional information; it can fuse multisource information and conduct experiments on it.

2. Application Method of Neural Network Based on Multisource Information Fusion in Production Cost Prediction

The basic neurons in the neural network are similar to the neurons in the neural network in the human body, because the artificial neural network model is an imitated biological neuron. The neuron model system is shown in Figure 1. The neuron unit consists of multiple inputs p_i, $i = 1, 2, \cdots, n$, and one output q_j. The intermediate state is represented by the weighted sum and correction value of the input signal, and the output is

$$Q_j(t) = f\left(\sum_{i=1}^{n} w_{ji} p_i - \varphi_j\right) .. \quad (1)$$

The threshold of the neuron is expressed as φ_j, w_{ij} is the connection weight coefficient, n is the number of input signals, Q_j is the output of the neuron, t is the time, and f is the output transformation function, as shown in Figure 2; there are three transformation function forms of f, which can be seen from the figure which are continuous and nonlinear [8].

The basic neuron model of neural network has three basic principles:

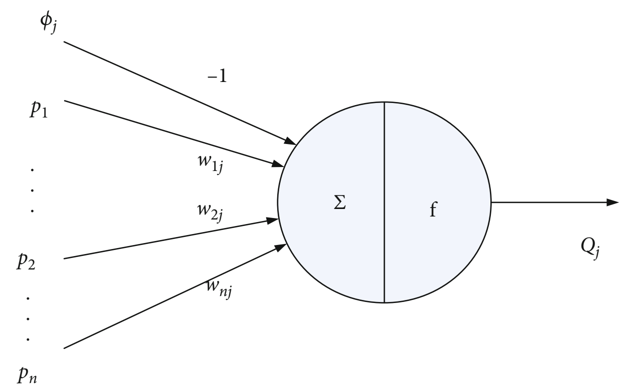

Figure 1: Neuron model.

(1) The connection function is required. The connection strength is expressed by the weight on the connection. When the weight is positive, it means activation, and negative value means inhibition

(2) A summation unit that calculates the sum of the magnitude (average line) of each input signal

(3) An activation function whose main purpose is to map and limit the size of neurons [9]

In fact, the process of human understanding of many realities is the process of compiling multisource information. People first perceive existing objects from multiple angles and places through sense organs such as the fingers, eyes, ears, and nostrils; then, the cognitive information that can be confirmed and matched with each other is released to the brain to improve the cognitive process in the brain and then obtain an accurate description of the factors, to the point of understanding [10]. This process of first visualizing and then developing knowledge is the process of human fusion of multisource information. Figure 3 roughly shows the basic flow of human information processing.

Multisensor information fusion using neural networks does not require any a priori information compared with the traditional fusion methods based on probability theory; it overcomes the defects of difficult-to-obtain and computationally intensive evidence in evidence-theoretic fusion methods. It not only broadens the ability of neural network to process information, so that it can handle both precise and imprecise or fuzzy information, but also, the trained neural network can fuse multisensor information without additional information, which improves the fusion capability of the fusion system as well as the accuracy of fusion. Here are the two neural networks used in this article.

2.1. BP Neural Network. BP (back propagation) network is a multilayer feedthrough neural network trained according to error generation algorithm, and it is one of the most widely used neural models [11]. Its main idea is to compare the results of receiving stimuli (weighting effect) with the expected results of receiving errors through training samples. It can be calculated that the error is caused by the influence of the input size and boundary, and then, we calculate

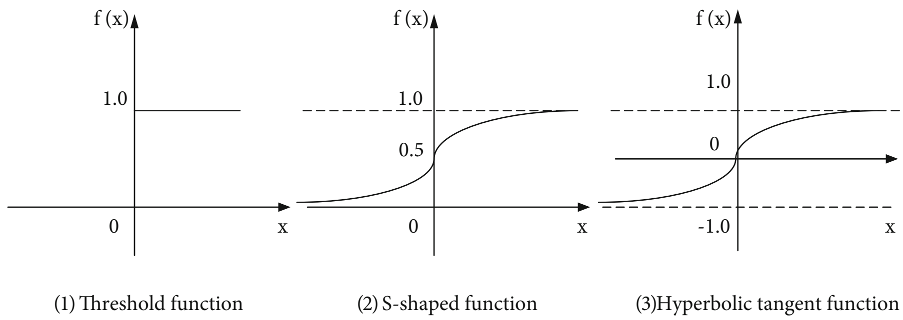

Figure 2: Common transformation (excitation) functions in neurons.

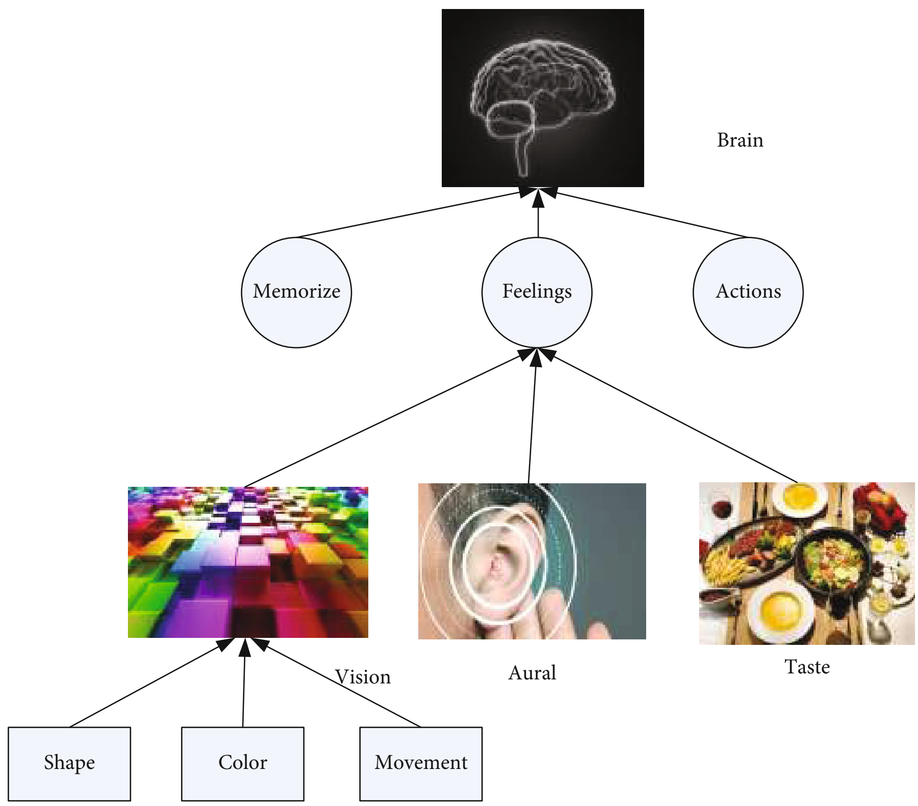

Figure 3: The way the cranial nervous system receives and processes signals.

the dimension and threshold of each layer in the network to adjust and correct until the result is as close as possible to the expected vector to end the training. This learning process is referred to as reverse spread [12]. After the propagation is completed, the weights and thresholds are determined, and the functional relationship between input and output is also determined. At this time, the neural network has the function of memory and prediction.

2.2. RBF Network. RBF neural network has only one hidden layer, so it can be regarded as a three-layer network structure, which belongs to the forward neural network model. The input layer is in the first layer of the network structure; the implicit layer is in the second layer, and the radial basis function is used for the transform function of the implicit layer; the last layer is the output layer, which does not do the same work as the implicit layer and has a different learning strategy. In the RBF network learning algorithm, there are three sets of parameters to be adjusted: the center of the basis function in the implicit layer, the variance, and the connection weights from the implicit layer units to the output units.

The RBF network mainly generates a hidden layer space in the basic structure. When the network starts to input, the input can be converted into the hidden layer space through the functional relationship, which avoids the connection function. Because as long as the center point of the RBF network is determined, the functional relationship is also determined, and the conversion of the input to the hidden layer space is linear; the output only needs to add the value of each hidden space; sigmoid is often used for the output of hidden layers [13]. On the whole, although the input to output of the neural network is not linear, the weight of the network is artificially controllable, which improves the training efficiency and avoids the problem of local minima. The generalization ability of RBF is better than BP network in many aspects, but the structure of BP network is simpler than RBF network when solving the problems with the same accuracy requirements. RBF network can approximate any nonlinear function with any accuracy and has the ability of global approximation. In theory, RBF network and BP network can approach any nonlinear function with arbitrary accuracy. The multisource information fusion in research is to simulate the complex process of human brain processing multisource data. In a system with multiple sensors, due to the different physical characteristics of the sensors, using these sensors to measure the same object will obtain measurement information under different systems. The multisensor fusion system can convert the measurement information under these different systems into the same coordinate system and then combine them according to the optimal signal to obtain comprehensive information of the object [14]. Multisource information aggregation, also called multisensor information fusion, is the process of processing data for multiple sensors or multiple data sources. It has the advantages of strong survivability, wide area, high reliability, high search performance, and low data collection cost, which is suitable for machine production [15]. Therefore, it is of great significance to broaden and deepen the scientific research of multisource data integration and the design of related algorithms based on multisource information fusion to solve existing problems.

In practical applications, in order to obtain more accurate results, multiple sensors can be used to measure the same object. However, due to the different physical characteristics of sensors, it is likely to cause differences in accuracy between sensors [16]. In this case, it can consider the process of measuring data by proportionally distributing the data of each sensor to obtain more accurate measurement values. The specific derivation process of the proportional distribution of sensor accuracy is as follows: first, consider two different sensors measuring the same object at time t; the results are, respectively,

$$\begin{aligned} U_{t_1} &= s_t + v_{t_1}, \\ U_{t_2} &= s_t + v_{t_2} \end{aligned} \tag{2}$$

Among them, t represents the time parameter, s_t represents the true value of the target, v_{t_1} and v_{t_2} represent the random error, and the random error satisfies $v_{t_1} \sim (0, F_{t_1})$, $v_{t_2} \sim (0, F_{t_2})$, and the measured values of the two sensors are independent of each other [17]. Assuming that the estimated value $\hat{s}_t$ of s_t has a linear relationship with the measured values z_{t_1} and z_{t_2}, since the estimated value $\hat{s}_t$ is an unbiased estimate of s_t, there is

$$\hat{s}_t = f_{t_1} z_{t_1} + f_{t_2} z_{t_2}. \tag{3}$$

f_{t_1} and f_{t_2} indicate the weight of the measured value of each sensor. At this time, the estimated error is

$$\tilde{s}_t = s_t \text{-} \hat{s}_t. \tag{4}$$

Using the cost function G to represent the root mean square error of $\tilde{s}_t$, then we have

$$G = E\left(\tilde{s}_t^2\right) = E\left[s_t - f_{t_1}\left(s_t + v_{t_1}\right) - f_{t_2}\left(s_t + v_{t_2}\right)\right]^2. \tag{5}$$

Since $\hat{s}_t$ is an unbiased estimate of s_t, we can get

$$E\left(\tilde{s}_t\right) = E\left[s_t - f_{t_1}\left(s_t + v_{t_1}\right) - f_{t_2}\left(s_t + v_{t_2}\right)\right]^2 = 0. \tag{6}$$

Because of $E(v_{t_1}) = E(v_{t_2}) = 0, E(s_t) = E(\hat{s}_t)$, it can get

$$f_{t_2} = I - f_{t_1}. \tag{7}$$

Among them, I is the proper-dimensional identity matrix. The cost function G can be rewritten as

$$G = E\left[\left(f_{t_1}\right)^2 (v_{t_1})^2 + \left(I - f_{t_1}\right)^2 (v_{t_2})^2 + 2\left(f_{t_1}\right)\left(I - f_{t_1}\right)(v_{t_1})(v_{t_2})\right]. \tag{8}$$

From$v_{t_1} \sim (0, F_{t_1}), v_{t_2} \sim (0, F_{t_2})$, and$v_{t_1}andv_{t_2}$which are independent of each other, we can get

$$\begin{aligned} E\left[\left(v_{t_1}\right)^2\right] &= F_{t_1}, \\ E\left[\left(v_{t_1}\right)^2\right] &= F_{t_1}, \\ E\left[\left(v_{t_1}\right)\left(v_{t_2}\right)\right] &= 0. \end{aligned} \tag{9}$$

Then,

$$G = E\left(\tilde{s}_t^2\right) = \left(f_{t_1}\right)^2 F_{t_2} + \left(I - f_{t_1}\right)^2 v_{t_2}. \tag{10}$$

In order to find the smallest cost function G, let $\phi = (f_{t_1}, f_{t_2})$ and derivate ϕ.

$$\frac{\partial G}{\partial \phi} = 0. \tag{11}$$

Solve the optimal weight:

$$\begin{aligned} f_{t_1} &= \frac{F_{t_2}}{F_{t_1} + F_{t_2}}, \\ f_{t_1} &= \frac{F_{t_2}}{F_{t_1} + F_{t_2}}. \end{aligned} \tag{12}$$

The best estimate is

$$\widehat{s}_t = \frac{F_{t_2}}{F_{t_1} + F_{t_2}} z_{t_1} + \frac{F_{t_1}}{F_{t_1} + F_{t_2}} z_{t_2} = \frac{F_{t_1} F_{t_2}}{F_{t_1} + F_{t_2}} \left(\frac{1}{F_{t_1}} z_{t_1} + \frac{1}{F_{t_2}} z_{t_2} \right). \quad (13)$$

The error covariance matrix after fusion is

$$F_t = \frac{F_{t_1} F_{t_2}}{F_{t_1} + F_{t_2}} = \left(\frac{1}{F_{t_1}} + \frac{1}{F_{t_2}} \right)^{-1}. \quad (14)$$

By analogy, if there are Q sensors, the corresponding measurement set and measurement noise matrix set are $\{z_{t_q}\}$ and $\{v_{t_q}\}$, respectively; $q = 1, 2, \cdots, Q$ is Gaussian white noise, which satisfies $v_{t_q} \sim (0, F_{t_q})$; and the noises are not correlated. According to the limit theory of multivariate function, the weighting coefficient corresponding to the measured value of each sensor under the minimum mean square error can be obtained.

$$f_{t_q} = \frac{1/F_{t_q}}{\sum_{q=1}^{Q} \left(1/F_{t_q} \right)}. \quad (15)$$

The error covariance matrix after fusion is

$$F_t = \left(\frac{1}{F_{t_1}} + \frac{1}{F_{t_2}} + \cdots + \frac{1}{F_{t_q}} \right)^{-1}. \quad (16)$$

The multisensor optimal estimate is

$$\widehat{s}_t = F_t \left(\frac{1}{F_{t_1}} z_{t_1} + \frac{1}{F_{t_2}} z_{t_2} + \cdots + \frac{1}{F_{t_q}} z_{t_q} \right). \quad (17)$$

Consistency fusion is an effective algorithm under a distributed structure. It refers to the interaction of information between each subject and neighboring subjects in a multiagent system. As a result, they influence each other, making the subjects gradually converge over time [18]. For research on consistency weighted fusion, graph theory is an important analysis tool. In a wireless sensor network, there are Q wireless sensors, which can be expressed as $H = (W, E)$. Among them, $W = \{1, 2, \cdots, Q\}$ represents the sensor node set, and $E \subset W \times W$ is the edge set. If the sensor node i and sensor node j can communicate, then

$$E_{ij} \subset E, \quad i = 1, 2, \cdots, Q; j = 1, 2, \cdots, Q. \quad (18)$$

According to whether the edges are directed, the network topology can be divided into directed graphs and undirected graphs. $\Omega_i = \{j : (i, j) \in E\}$ represents the set of communicable neighbors of sensor node i. The communication conditions between all nodes can be represented by Laplacian matrix A, and the elements of Laplacian matrix are expressed in the following form:

When $i = j$,

$$a_{ij} = \sum_j c_{ij}. \quad (19)$$

When $i \neq j$,

$$a_{ij} = -c_{ij}. \quad (20)$$

If $E_{ij} \subset E$, then $c_{ij} > 0$; otherwise, $c_{ij} = 0$. If the network topology is an undirected graph, then $c_{ij} = c_{ji}$; at this time, A is a symmetric matrix, all its eigenvalues are real numbers, and there is only one zero eigenvalue α_1. The algebraic connectivity of the network is closely related to the nonzero minimum eigenvalue α_2. The larger the α_2 is, the better the connectivity between sensor nodes in the network structure, and the faster the system will converge. The form of consistency weighted fusion is shown below [19].

$$s_{(t+1)_i} = s_{t_i} + \beta \sum_{j \in \Omega_i} c_{ij} \left(s_{t_j} - s_{t_i} \right). \quad (21)$$

Among them, $0 < \beta < 1/\Delta$ is the step size, $\Delta = \max_i(\sum_{j \neq i} c_{ij})$. It can be seen from the above formula that if the topological structure is always the same and the network connection is an undirected graph, then each subject in the system will evolve toward the state of the neighboring subject. The information of each subject is transferred and transformed according to the consensus algorithm. When$t \longrightarrow \infty$and$(s_{t_j} - s_{t_i}) \longrightarrow 0, \forall i \neq j$, then all subjects in the system will eventually converge, reaching the weighted average of the initial value.

In wireless sensor networks, a large number of wireless sensors are used to measure the same object, and then, the measurement data is combined by a central or distributed system to achieve the purpose of accurate tracking [20]. However, due to the limitations of the sensor's own application conditions, traditional centralized systems are not suitable for wireless sensor networks to optimize services in complex environments. In an integrated system, all sensor components in the network are information processing centers, and only the sensor components exchange information with neighboring components. Compared with centralized systems, distributed systems have obvious advantages in terms of network communication and computational complexity, and integrated systems can better adapt to interference such as packet loss and long delay.

The neural structure based on the multisource information fusion system used in this paper is shown in Figure 4 [21]. Production cycle, factory scale, production complexity, production efficiency, etc. can be measured offline and have an extremely close relationship with product cost, which is used as the input of the neural network.

The hierarchical modular neural network fusion model is composed of multisensor unit MSU (multisensor unit), task decomposition unit (TDU), neural network submodule SMNNU (submodular neural network), and fusion

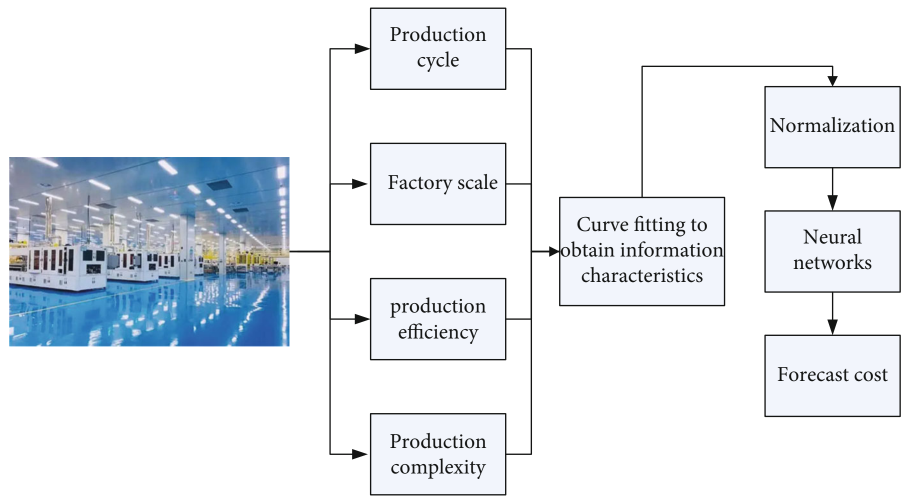

Figure 4: Multi-information fusion structure diagram based on neural network.

synthesis unit (fusion synthesis unit), as shown in Figure 5 [22]. Among them, the neural network submodule SMNNU can be integrated by a small neural network composed of multiple neural networks in parallel. The basic idea is that in the learning phase, the sensor unit will preprocess the detected signal and send it to the TDU, where the learning sample space is decomposed into several sample subspaces; an SMNNU is constructed for each subspace, and learning is performed. In the working stage, TDU is used to determine the degree of membership of the data to each subspace. FSU dynamically selects some or all of the SMNNUs to work according to the degree of membership and integrates the processing results of the selected SMNNUs in a weighted sum [23].

2.3. Production Cost Forecast

2.3.1. The Concept of Production Cost. Production cost refers to the cost of manufacturing services, that is, the cost incurred by an enterprise to produce a product. For each product price, production costs belong to all related costs that occur in a specific production stage, as shown in Figure 6. Compared with the cost of other steps, the entire production process includes uncertain factors of raw materials, technological processes, and labor. Therefore, the calculation and prediction of production costs will become complicated and important [24].

Because the object of production is generally a product, a product is a combination of related behaviors or interactions that transform inputs into production. We can see that the meaning of products is very broad. For different companies, product cost allocation and manufacturing processes are also very different. As far as traditional manufacturing is concerned, the main characteristics of its production are multistep, medium-scale production; a large proportion of simulation work in the manufacturing process; and low automation. Compared with other automated production lines such as automobile production lines, it has more complex uncertainties.

Cost forecasting is very important to enterprises and to a certain extent determines the efficiency and knowledge of market pricing, cost analysis, and management. At present, the main cost estimation methods include parameter method, comparison method, and analysis method. Parametric methods use experience and statistics to decompose each key feature of the product, analyze the functional relationship between each key parameter and cost, and then use dynamic analysis to make cost forecasts. This method is simple and fast, but the accuracy rate is not very high [25]. The main manifestations of the comparative method are cluster analysis and case-based thinking methods, which are most suitable for forecasting and estimating with rich historical data and significant similarity. Compared with the above two methods, the analysis method is mainly through the analysis and modeling of the basic elements of the product and market capabilities and further enhances the resulting cost forecast results.

2.3.2. Principles of Production Cost Forecasting. For the special time-space relationship of each product, it is required that the prediction of production cost must comprehensively consider time factors, space factors, and related policy factors, and with the development of science and technology, the production of various products will gradually mature. The purpose of forecasting production costs is to strengthen cost management, pay attention to cost forecasts, and strengthen the study of cost forecasting theory, so as to reduce production costs and improve economic benefits of enterprises. In order to make the predicted results more reasonable, the production cost forecast should follow the following basic principles [26].

2.3.3. Scientific Principles. In the calculation of production cost, the choice of cost factors must be scientific, the definition and extension must be refined, and the corresponding response must also appear in the forecasting system. If the cost object is determined incorrectly or inaccurate cost calculation tools are used, the problem of cost calculation will be greatly increased.

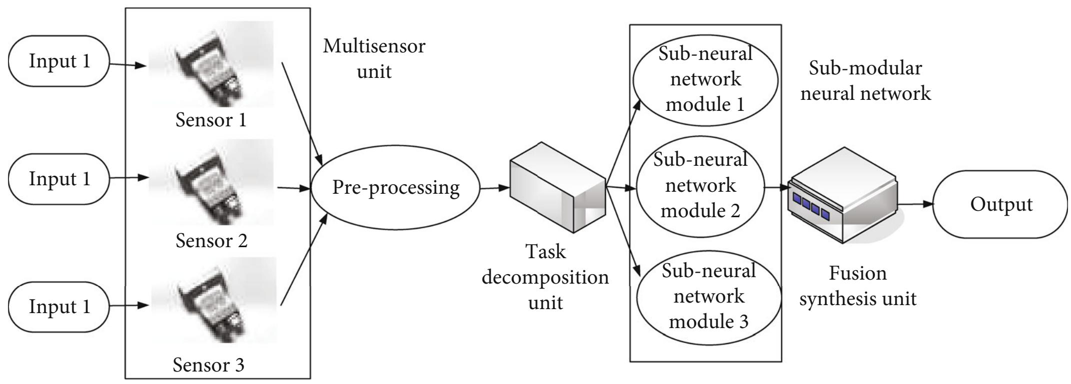

Figure 5: Information fusion model of modular neural network integration.

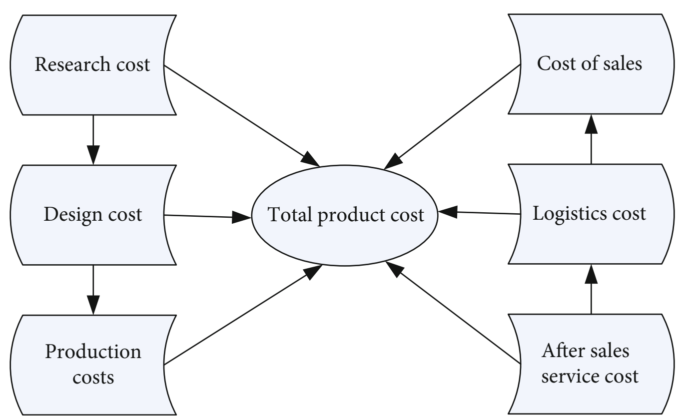

Figure 6: Description of total product cost and total production cost.

Table 1: Classification of production cost items.

Serial number	Main influencing factors	Production cost item	Cost proportion
1	Time and space factors	Expenditure on raw materials, electricity, repair, and production site	35%~50%
2	Time factor	Wages and benefits, depreciation	30%~45%
3	Policy factors	Quality inspection fee and maintenance fee	5%~10%
4	Other factors	Other expenses	5%~10%

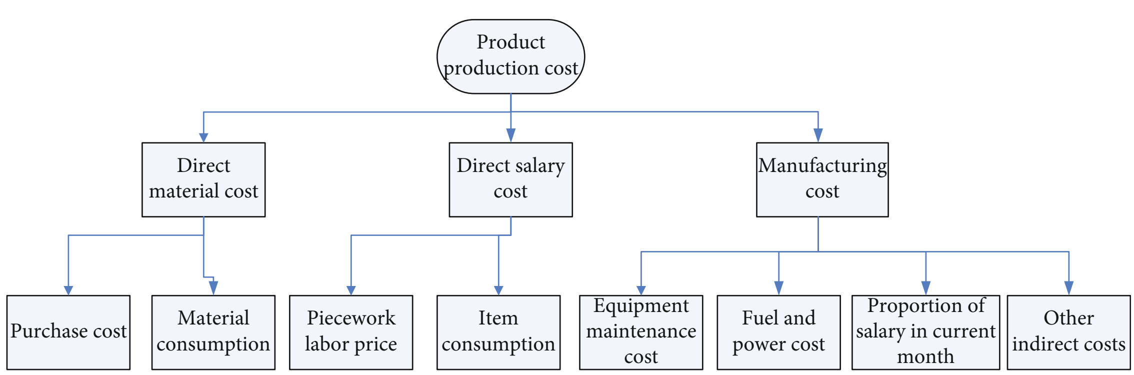

Figure 7: Qualitative structure diagram of product production cost prediction model.

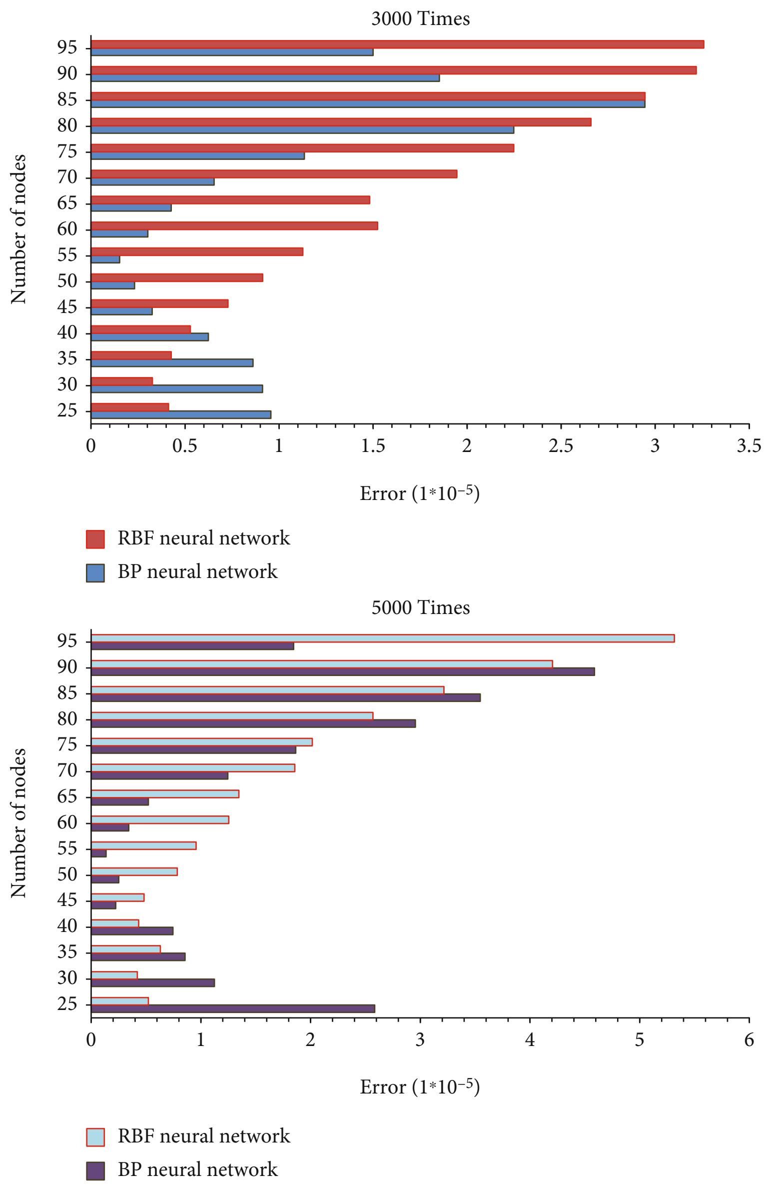

FIGURE 8: The influence of hidden nodes on the training error of the number of nodes.

2.3.4. The Principle of Comprehensive Rationality. In order to be more comprehensive and better reflect the value of the product in the manufacturing process, the selection of materials requires comprehensive thinking and requirements, so that cost analysis can provide relatively rich information. When designing a forecasting system, it is necessary not only to calculate the total cost and individual cost of the product but also to distinguish the total cost according to the reason to reflect the summary and system of market value. In this way, it is not only easy to manage production costs but also easy to analyze the system benefits in production and calculate the production department [27].

2.3.5. The Principle of Feasibility. The cost objects listed in the feasibility requirements must be realized. The first is to keep the selection of objects consistent with the relevant departments, and the maximum extent of statistical data should be used. Secondly, the selected indicators must be measurable and quantifiable.

2.3.6. Coordination Principle. The manufacturing process is complex, and there is always more than one purpose to make a budget, more than one product is produced, and more than one material for cost accounting. Therefore, after payment, it is usually not directly and completely credited to the account of the identification project, and a system is required to allocate the cost to several things. At the same time, the system must also consider the cost difference of the same product on the production line and the cost difference of different types on the same production line. In this way, the correction system is also reduced to facilitate the application of prediction and maintain the degree of freedom of the same level of objects. This process cannot be

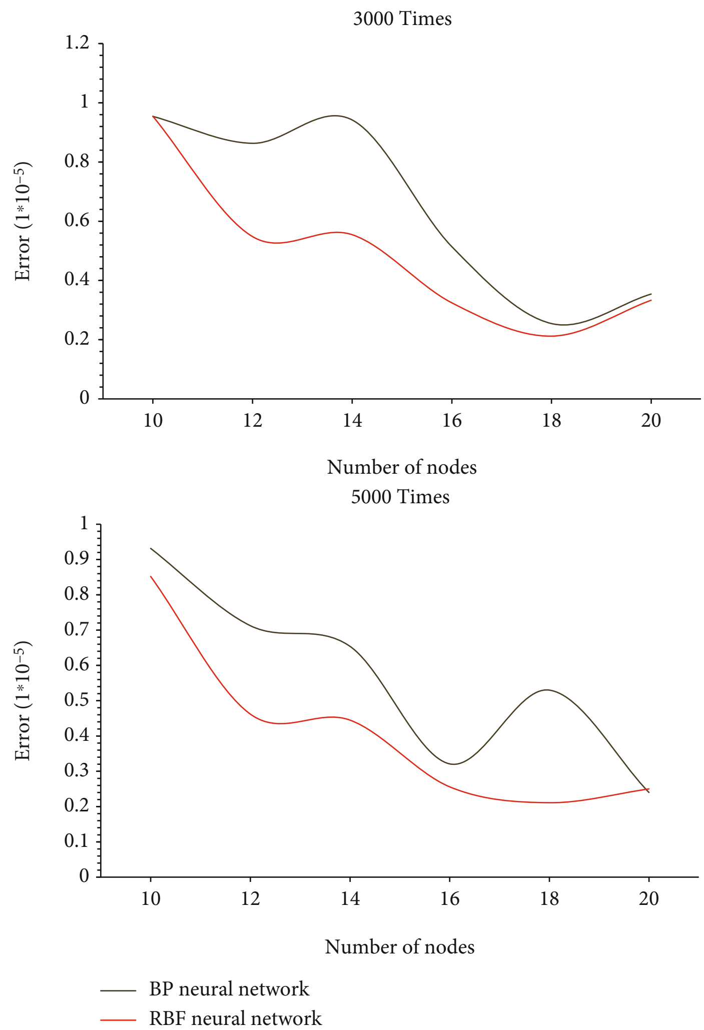

Figure 9: The influence of the number of training sample sets on the model prediction error.

Table 2: The true value of various costs in the production model.

Costs spent on items	Cost actual value (million yuan)	Costs spent on items	Cost actual value (million yuan)
Direct material cost	10.23	Total wage	25.31
Stuff consume price	12.45	Living expenses	0.5
Cost of fix	0.23	Indirect cost	1

considered in isolation, but it must be planned together with the probability model.

2.3.7. The Principle of Associativity. The principle of integration should combine qualitative analysis and quantitative analysis and plan production costs according to different companies and different regions. Since the locations of several companies are very different, it is impossible to have a unified model for specific charging calculation methods. After a long process, many commonly used cost accounting methods have been formed, namely, the variety method, the batch method, and the step method. If the company's products are not produced in stages, but only one step, all product varieties can be directly used as cost accounting tools. This is the variety method. If the product is divided into several steps or several batches, it is a batch method. If the intermediate is a semifinished product and the product is mass-produced, the finished product and the completion of each step are for the cost calculation object; this method is called the step-by-step method. When the production cost is only for forecasting, it should be planned according to the characteristics of the company to be effective.

3. Establishment of Production Cost Prediction Model

3.1. Establishment and Quantification of Index System. There are many factors that affect production costs. To sum up, production cost is the cost down a series of production activities and consists of three components: direct materials,

Table 3: Comparison of BP neural network and RBF network total production cost prediction results.

	True value	Predicted value	
		BP neural network	RBF networks
Total production cost	49.72	48.25	49.12
Predicted difference	0	1.47	0.6
Prediction error	0	0.0296	0.0121

Table 4: Comparison of prediction results of total production cost of BP neural network and RBF network.

	Average accuracy rate	Highest accuracy rate	Time (s)
BP neural network	0.7785	0.8724	864
RBF networks	0.8512	0.9201	852

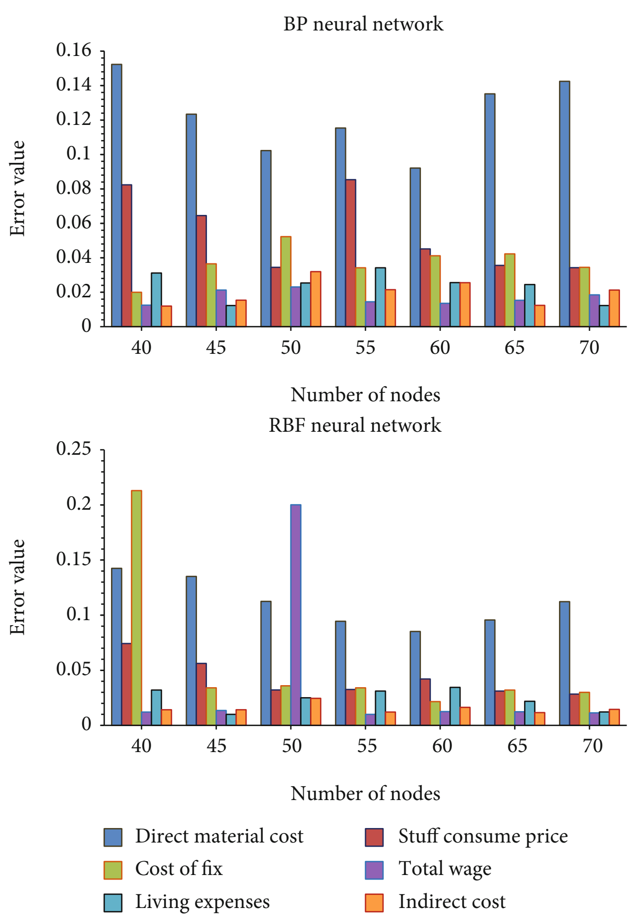

Figure 10: BP neural network and RBF network production cost prediction results.

direct labor, and manufacturing overhead; the forecast of production costs mainly considers space and time factors that affect production costs. Regarding the time factor, due to the very complicated impression factors in different periods, coupled with the human factor of historical data, we do not specifically analyze the time influencing factors. The spatial factors of production costs mainly include location conditions and natural disasters. The unascertained evaluation model is used to determine the complexity coefficients of these influencing factors in product production, so as to analyze the influence of spatial factors. The policy factors are directly calculated according to the current financial system. Therefore, the cost items can be classified according to the main influencing factors, as shown in Table 1.

Among them, type 1 cost items consider not only the impact of space factors but also time factors; type 2 cost items mainly consider the impact of time; type 3 cost items are determined according to the financial policies of the country and the enterprise.

3.2. Cost and Quality Relationship System and Impact. With the passage of time and the development of the company, there will also be manufacturing cost factors that cannot be controlled as the primary control, or from uncontrollable to controllable, which can meet industry growth needs and cost forecasts. In summary, the current production cost and quality relationship system and influencing variables of the manufacturing industry are shown in Figure 7.

The parameters and formulas of the model are described as follows:

(1) Product production cost prediction model variables

(i) Direct material cost (DMC) = material purchase price (MPP) ∗ material consume (MC)

(ii) Item consumption cost, stuff consume price (SCP)

(iii) Equipment maintenance cost, cost of fix (CF)

(iv) Total salary for the month, total wage (TW)

(v) Living expenses (LE)

According to the above description, the above are uncontrollable variables, and the remaining are indirect cost (IC).

(2) Based on the above forecast model variable analysis and cost accounting system, a cost forecast model can be obtained

$$W = \sum \mathrm{DMC}_n + \sum \mathrm{SCP}_n + \sum \mathrm{CF}_n + \sum \mathrm{TW}_n + \sum \mathrm{LE}_n + \mathrm{IC} \quad (22)$$

Among them, $\sum \mathrm{LC}_n$ is the sum of labor wages for manufacturing the product.

BP network is the most widely used in neural network, and there have been many successful application examples of BP network. This article will use the BP network and the RBF network to integrate the multisource information that affects the production cost.

4. Neural Network Based on Multisource Information Fusion in Production Cost Prediction

The selection of the number of hidden layer nodes has a certain impact on the learning and performance of the BP network, but there is no certain principle or law to follow in the selection of the number of nodes. It is necessary to obtain a suitable number of hidden layer nodes through continuous attempts. Use the training sample set to train the neural network with different hidden layer nodes, and the training error based on the same training times (3000, 5000 times) is shown in Figure 8. Applying the trained prediction model to the test sample set, the prediction result shown in Figure 9 can be obtained.

It can be seen from Figure 8 that when the number of nodes is too few or too many, the error obtained by training the number of model nodes is relatively large, and the highest value has reached $5.3162e^{-5}$. When the number of training sample sets increases, the prediction errors of the BP neural network model and the RBF network model both show a downward trend, and the performance of the RBF network model is better than that of the BP neural network model. In order to further explore the quantitative relationship between the various cost prediction results and the true value in the production model, a neural network with 40 to 75 nodes is selected for exploration. Among them, Table 2 is the true value of various costs in the production model; the influencing factors of different cost categories are different. Through the comparison of the prediction results of six main production cost categories, the most suitable neural network is judged. Table 3 is the comparison of the production cost prediction results of the BP neural network and the RBF network, and Table 4 is the comparison of the total production cost prediction results. Figure 10 is the production cost prediction results of BP neural network and RBF network.

$$\text{Forecast error} = \frac{\text{true value-forecast result}}{\text{true value}}. \quad (23)$$

From Figure 10, it can be found that for the six cost categories, the RBF network is closer to the true value than the BP neural network, and it shows a higher predictive ability. Among them, the error of the RBF network in predicting the total salary of the current month is 0.01004. The prediction result of the RBF network is slightly better than that of the BP network, and the training process is much simpler, which is more suitable for realizing multisource information fusion. And the two kinds of neural networks have large errors in direct material costs, item consumption costs, living expenses, and other indirect costs. For example, in the direct material cost prediction, the error of the prediction result of the BP neural network is 0.1523, and the error of the prediction result of the RBF network is 0.1425. The source of large errors is related to the large fluctuations in direct material costs, because the cost of direct materials is uncontrollable in many aspects, such as commodity prices and customer purchases which are important factors that lead to changes in direct material costs. The neural network has powerful training and customization capabilities, strong resilience, and fault tolerance, and the neural network adopts a parallel structure and distributed storage, which can quickly realize the nonlinear mapping of system input to output. According to a certain learning method and a specific topological structure, the neural network can quickly grasp the knowledge of the sample through offline learning of a large number of samples. The connection weights and thresholds are stored, and the trained neural network can be used to quickly realize the fusion of the input information of the system and output the fusion results in a timely manner. Modern technology is becoming more and more complex, and the information provided by multiple sensors can effectively improve the accuracy requirements of a single sensor for target estimation.

5. Conclusion

The development of multisensor information fusion technology has improved people's ability to obtain various information. How to comprehensively process the obtained information to obtain accurate and reasonable estimates and decisions has become a practical problem that people urgently need to solve. Information fusion technology is a comprehensive information processing technology born to meet this social demand. Product cost prediction is of vital importance to enterprises and to a certain extent determines the effectiveness and scientificity of product pricing, cost analysis, and management. With the development of modern technology, multisource data fusion will surely become an important means of intelligent control and data processing for complex production equipment and advanced weapon systems in the future. Since information fusion is an emerging discipline, its development and application have just begun, coupled with the complexity of theory and technology, so there is no comprehensive performance test and evaluation method at present; the establishment of the design and evaluation method of the information fusion system and the correct evaluation of the results of multisource data fusion are of great significance to the application of information fusion. It should be said that this is the future development direction of information fusion technology. In practical applications, it is also necessary to add neural network modules as needed to improve tracking and prediction capabilities.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this article.

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