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Retraction

Retracted: Integrated Evaluation of Corporate Investment Decision Performance Based on Fuzzy Sets and BP Neural Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] J. Du, "Integrated Evaluation of Corporate Investment Decision Performance Based on Fuzzy Sets and BP Neural Networks," *Journal of Sensors*, vol. 2022, Article ID 7628124, 7 pages, 2022.

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Research Article

Integrated Evaluation of Corporate Investment Decision Performance Based on Fuzzy Sets and BP Neural Networks

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Enterprise investment decision performance evaluation is a complex system, which is affected by many factors. Based on the consideration of corporate strategy and stakeholders, a six-level index system is designed to evaluate the performance of corporate investment decision-making. The index-selection method combining benchmarking management and principal component analysis is established, and the enterprise management index analysis method based on neural network and fuzzy decision-making is designed. The multiattribute decision-making problem in enterprise performance evaluation is solved by using the triangular fuzzy-weighted Einstein-Bonferroni mean (TF-WEBM). The algorithm is suitable for multiattribute decision-making in a triangular fuzzy environment. Finally, the effectiveness of this method is verified by an enterprise performance evaluation example.

1. Introduction

The evaluation of enterprise investment decision performance is very important to the implementation of enterprise strategy, and strategic motivation is the most important motivation to evaluate enterprise investment decision performance [1]. Corporate governance is an important aspect that affects the performance evaluation of corporate investment decision-making, and the stakeholder corporate governance model is the development trend of corporate governance. Based on these two basic theoretical motivation assumptions, we discuss the performance evaluation index system of enterprise investment decision-making [2]. As an important tool for strategy implementation, enterprise performance evaluation inevitably varies from enterprise to enterprise and from stage to stage. It is a multilevel complex system [3].

Strategic management focuses on how to make enterprises use appropriate strategies to maintain competitive advantage. Its competitive situation has increased exponentially in recent years. However, Zhang et al. [4] pointed out that strategic management research has been criticized for paying too much attention to analysis. In addition, its high management preference, neglect of learning behavior, and insufficient attention to learning behavior are also the main reasons for criticism [5]. It is pointed out that the focus of organizational learning research is the process, which may be a disadvantage in providing insights. Muriana et al. [6] argued that organizational learning is the basis for achieving sustainable competitive advantage and is a key variable for improving business management. Ang and Quek [7] stated that companies that are able to learn have a better chance of perceiving events and trends in the marketplace.

In addition, several studies provide evidence of a positive correlation between organizational learning and firm performance. For example, Kuo et al. [8] found that the direction of learning had a direct impact on firm performance [9]. Similar results were obtained by Wang et al. [10] using a cultural learning approach. Corporate performance appraisal is not only a result of a certain stage of market economy development, it is also a scientific approach and an effective tool that provides a role in regulating companies in a mature market economy [11]. While learning from successful business management experiences in foreign market economies is the direction of modern business management, the application of business performance assessment to the supervision and control of enterprises is also an important tool.

As one of the tools of modern corporate management, performance assessment is being tested by the rapid development of the economy and the constant renewal of corporate management models and is receiving wider attention and more in-depth discussion [12].

For China's enterprise performance appraisal work, understanding how to comply with the changes in China's economic and social environment and international trends and establishing a performance appraisal system suitable for China's economic development are effective ways to improve enterprise performance [13]. At the same time, the enterprise performance appraisal system has particularly important business significance in improving the health and management level of enterprises, enhancing their competitiveness, and further improving the quality of economic development [14].

Therefore, enterprise performance assessment based on the triangular fuzzy information is a classical multiattribute decision problem [15]. In this paper, we study the multiattribute decision problem of enterprise performance evaluation under the triangular fuzzy information. We develop a process for multiattribute decision-making in a triangular fuzzy environment using the triangular fuzzy-weighted Einstein-Bonferroni mean (TF-WEBM) operator. Finally, an example of enterprise performance evaluation is given to validate the developed method [16].

2. Construction and Selection of Indicator Systems

2.1. Construction of the Indicator System. Based on the strategy and stakeholder theory, the evaluation of shareholders, employees, related enterprises (upstream and downstream enterprises), society, and intellectual capital are integrated into the evaluation index system. The frequency statistics method, theoretical analysis method, and expert consultation method are used to set and screen the indicators, adjust the indicators, and establish a general indicator system for evaluating the performance of corporate investment decisions [17].

NPV is based on option NPV+C(value of the option),($C = At.N(d1) + I_t e^{-Rt}.(d2)$, = present value of investment return =Atexercise price of option= $\sum_{10+1}^{T} A(t).(1+r)^t$, I_t= additional investment$I_t(0)$; $d1 =$ $[I_n(\text{At}/I_t) + (R + \sigma^2/2t]/$ $(\sigma.t^{1/2})d2 = d1 - \sigma.t^{1/2}$; R the risk rate; r is the risk discount rate; $A(t)$ is the net cash flow; σ is the expected return volatility; t is option maturity time), modified economic value added (REVA), return on intellectual capital, modified internal rate of return (RIRR), intellectual capital efficiency contribution rate, capital conservation and appreciation rate, net sales margin, payback period, cost reduction rate, earnings per share, current asset turnover, accounts receivable turnover, inventory turnover, ratio of net cash flow to REVA, asset-generating rate, net asset-generating rate, cost margin, net cash flow, return on debt, cost reduction rate, upstream corporate cost profitability, growth rate of knowledge, and intellectual assets contribution value [18].

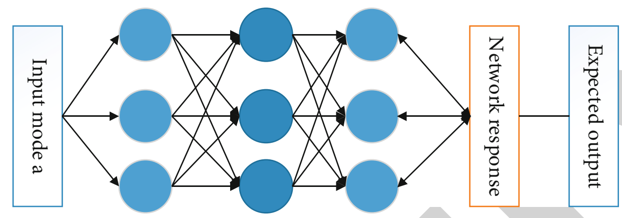

Figure 1: Neural network structure.

2.2. Benchmarking-Based Indicator System Screening. There are many mathematical methods for selecting indicators for evaluating the performance of enterprise investment decisions, including affiliation analysis, correlation analysis, discriminative power analysis, and grey correlation analysis. The principal component analysis is used here to select indicators at each level. The principal component analysis requires a large number of samples, and the company's own historical data is easy to obtain and can meet the conditions, in line with the principles of cost minimisation and efficiency. Using the principal component analysis, k principal components are obtained, and the variance contribution of the k values is determined by $\sum_{g=1}^{k} \lambda_g / \sum_{g=1}^{p} \lambda_g$ retaining 85%. The indicators in the retained principal components are judged, and those with smaller coefficients are screened out, while those with larger coefficients are retained, i.e., the principal component indicators. In the practice of investment decision performance of enterprises, it should be determined in conjunction with the theory and practice of enterprise management.

3. Fuzzy Integrated Evaluation Model

The factors affecting the performance of investment decisions are divided into several subsystems according to the attributes of the objectives, the evaluation set U is composed of all evaluation indicators, and the set of evaluation indicators is divided into n subsets according to each objective that cannot be subdivided, $U = \{U_1, U_2, \cdots; U_n\}$, and satisfies

$$\bigcup_{i=1}^{n} U_i \neq U, U_i \cap U_j = \varnothing (i \neq j \quad i, j \in \{1, 2, \cdots; n\}). \tag{1}$$

Let the i-th subset be $U_i = u_{i1}, u_{12}, \cdots; u_{ik}\}$; then the characteristic values of the evaluation indicators of the m samples can be represented by the following matrix:

$$\begin{aligned} X(i) &= \begin{bmatrix} x_{11}(i) & x_{12}(i) & \cdots & x_{1m}(i) \\ x_{21}(i) & x_{22}(i) & \cdots & x_{2m}(i) \\ & \cdots & & \\ x_{k1}(i) & x_{k2}(i) & \cdots & x_{km}(i) \end{bmatrix} \\ &= [X_1(i), X_2(i), \cdots X_k(i)] \\ &= [x_{kj}(i)] x_m, \end{aligned} \tag{2}$$

where $X_k(i) (k \in \{1, 2, \cdots; h\})$ represents the eigenvectors of

Table 1: Data for evaluating the performance of corporate investment decisions.

Project	Index								
	A1	A2	A3	A4	A5	A6	A7	A8	A9
1	0.055	0.24	0.25	0.87	0.07	0.08	0.07	0.12	0.75
2	0.087	0.55	0.27	0.90	0.11	0.88	0.06	0.27	0.78
3	0.07	0.40	0.035	0.81	0.13	0.70	0.074	0.25	0.81
4	0.05	0.45	0.037	0.87	0.27	0.72	0.078	0.26	0.88
5	0.08	0.48	0.057	0.89	0.37	0.78	0.074	0.27	0.89
6	0.09	0.50	0.058	0.90	0.40	0.79	0.075	0.30	0.90

the m samples corresponding to the indicators $U_{ik} \in U_i$ and $X_k(i) \neq (x_{k1}(i), x_{k2}(i), \cdots x_{km}(i))$.

According to the different types of evaluation indicators (cost, benefit, moderate, interval, etc.), different affiliation functions are used to transform the matrix of eigenvalues into the following affiliation matrix (evaluation matrix).

$$R(i) = \begin{bmatrix} r_{11}(i) & r_{12}(i) & \cdots & r_{1m}(i) \\ r_{21}(i) & r_{22}(i) & \cdots & r_{2m}(i) \\ & \cdots & & \\ r_{k1}(i) & r_{k2}(i) & \cdots & r_{km}(i) \end{bmatrix} = R_1(i), R_2(i), \cdots ; R_k(i)] = l_{kj}(i) l_{k\times m}, \tag{3}$$

where $r_{kj}(i)$ is the affiliation of the sample p_j corresponding to u_{kj} of u_i and $r_{kj}(i) \in [0, 1]$; $Rj(i)$ is the one-sample evaluation of the h indicators corresponding to p_j and $Rj(i) = (r_{1j}(i), r_{2j}(i), \cdots ; r_{kj}(i))^T$.

Let the weight coefficients of the k indicators of the subset u_i be $A(i) \neq (a_1(i), a_2(i), \cdots ; a_k(i))$ as the value of the weight coefficient corresponding to the k-th evaluation indicator and

$$a_k(i) \geq 0, \sum_{k\neq j}^{h} a_k(i) = 1. \tag{4}$$

4. Triangular Fuzzy Information Theory

This section will briefly introduce some basic concepts and fundamental operations related to trigonometric fuzzy numbers.

Definition 1. A triangular fuzzy number a can be defined by a triplet as (a^L, a^M, a^U). The membership function is defined as

Table 2: Fuzzy integrated evaluation and BP neural network model training results.

Project	Actual output	Ideal output	Achievements
1	0.6425	0.65478	Medium
2	0.9478	0.9587	Excellent
3	0.8714	0.9478	Good
4	0.5741	0.5471	Poor
5	0.5781	0.5897	Poor
6	0.9001	0.9854	Excellent
7	0.9547	0.9247	Excellent
8	0.5574	0.5587	Poor
9	0.8241	0.8574	Good
10	0.5741	0.5574	Medium

$$\mu(x) = \begin{cases} 0, & x < a^L, \\ \dfrac{x - a^L}{a^M - a^L}, & a^L \leq x \leq a^M, \\ \dfrac{x - a^U}{a^M - a^U}, & a^M \leq x \leq a^U, \\ 0, & x \geq a^U, \end{cases} \tag{5}$$

where $0 < a^L \leq a^M \leq a^U, a^L$ and a^U denote the lower and upper limits of $\tilde{a}$, respectively, and a^M denotes the modal value.

Definition 2. Let $\tilde{b} = [b^L, b^M, b^U]$ and $\tilde{a} = [a^L, a^M, a^U]$ be two triangular fuzzy numbers; then the degree of probability that $a \geq b$ is

$$p(a \geq b) = \lambda \max 1 - \max \frac{b^M - a^L}{a^M - a^L + b^M - b^L, 0} (1 - \lambda) \max \left\{ 1 - \max \left[\frac{b^U - a^M}{a^U - a^M + b^M - b^M}, 0 \right], 0 \right\}. \tag{6}$$

The λ value is an indicator of the attitude of the rating, which reflects the risk attitude of the decision-maker. If $\lambda > 0.5$, the decision-maker is a risk lover; if $\lambda = 0.5$, the

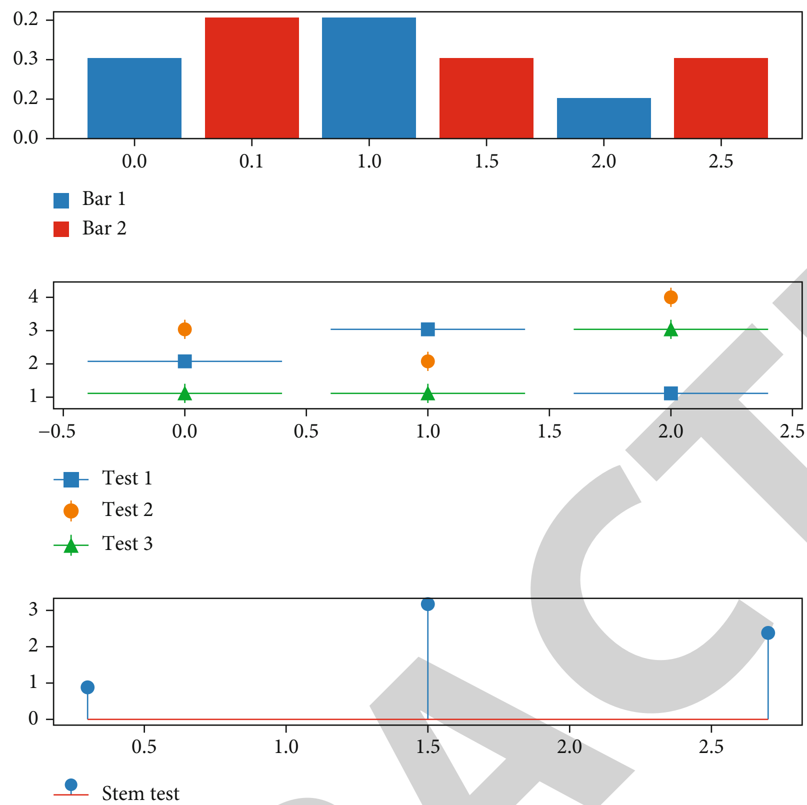

Figure 2: Development utilisation rates of different companies.

decision-maker is risk-neutral; if $\lambda < 0.5$, the chooser is risk-averse.

However, the Bonferroni mean (BM) operator and the Einstein operator are usually used in cases where the input parameters are nonnegative real numbers. Kumar and Ravi [16] extended the BM and Einstein operators to accommodate the case where the input parameters are triangular fuzzy numbers and proposed the triangular fuzzy Einstein-Bonferroni mean (TF-EBM) operator.

Considering that the input parameters may have different importance, Zhang et al. [19] further proposed the triangular fuzzy-weighted Einstein-Bonferroni mean (TF-WEBM) operator.

Definition 3. $a_i = [a_i^L, a_i^M, a_i^U](i = 1, 2, \cdots, n)$ is a set of triangular fuzzy numbers, and $p, q > 0, \omega = (\omega_1, \omega_2, \cdots, \omega_n)^{\mathrm{T}}$ is a weight vector of $a_i = [a_i^L, a_i^M, a_i^U](i = 1, 2, \cdots, n)$; ω_i expresses the importance of $\tilde{a}_i$, $\omega_i > 0(i = 1, 2, \cdots, n)$, and $\sum_{i=1}^{n} \omega_i = 1$.

5. A Comprehensive BP Neural Network Evaluation Model Based on Fuzzy Evaluation

The artificial neural network is a complex network composed of a large number of widely connected simple information units (called neurons). It is used to simulate the structure and behavior of the human brain neural network. The neural network is good at making decisions in approximate, uncertain, and even conflicting knowledge environments. Theoretically, the three-layer BP network can approximate any mapping relationship with any accuracy (Figure 1) [17, 20].

The number of neurons in the middle layer is determined according to the empirical formula $p \leq n \times (q + 3) + 1$. The input layer weight factor w_{ij} and the output layer weight factor v_{jt} are adjusted by a large number of sample training. The input of the intermediate layer unit is $s_j = \sum_{i \neq 1}^{n} W_{ij} a_i - \rho$, and the output of the intermediate layer is the connection right of the input layer to the intermediate layer; θ_j is the threshold of the intermediate layer unit; p is the number of intermediate units; n is the number of input layer units; q is the number of the output layer. The neuron transformation function $f(x)$ is a sigmoid function. Following the same propagation idea, the input L_t and output C_t of the middle layer are calculated [18, 21, 22].

$\Delta_{v_{jt}} = \alpha . d_{t\,b}^{k^k}, \Delta_t \gamma = \alpha . d_t^k, \Delta w_{ij} = \beta . e_j^k . \alpha_i^k, \Delta j_\theta = \beta \cdot e_j^k$ is the connection weight from the middle layer to the output layer and the threshold value of the output unit. The neuron feedback correction formula is as follows: α and β are the learning efficiency coefficients between 0 and 1, and k is the number of sample coefficients, where $d_t^k = (y_t^k - C_t^k) f'(L_t)$, $e_j^k = [\sum_{t \neq}^{q} v_{jt} d_t^k] f'(s_j)$. The use of the additional momentum method $(\Delta_W(N) = \mathrm{d} + \eta_W(N - 1)$ (η is the momentum

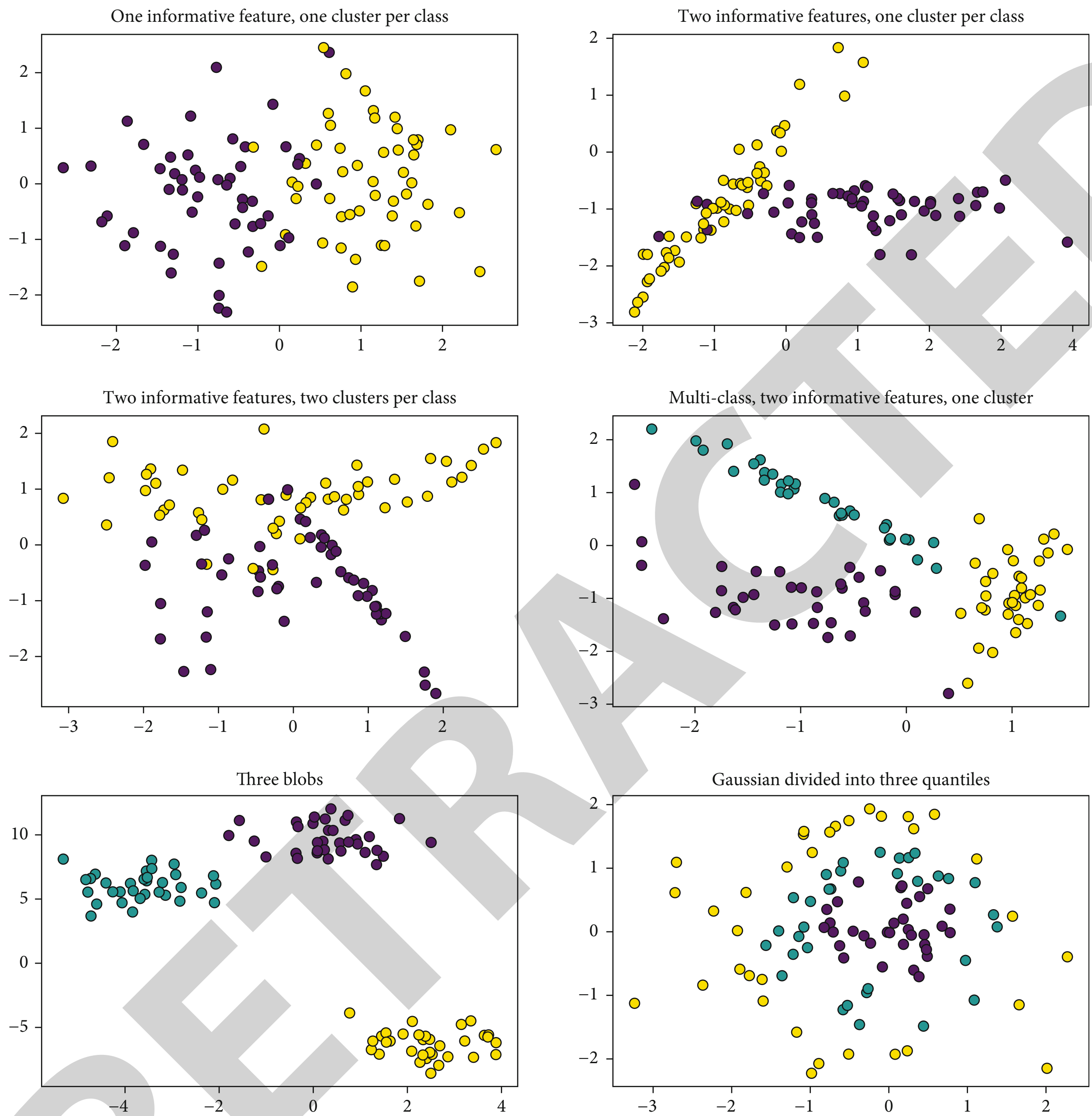

Figure 3: Cluster analysis of customers from different companies.

factor, generally between 0.9 and 0.98) can prevent the emergence of local minima and accelerate the convergence process of network learning and training.

The trained neural network is stored in the knowledge base for evaluating other evaluation objects. The result (vector) can be obtained by inputting the value vector (matrix) of the attribute of the object to be evaluated. Therefore, the neural network at this time is called the neural network comprehensive evaluation model. The connection weight coefficient and internal threshold of the neural network are the model parameters. Fuzzy evaluation samples and evaluation results provide training samples for the training of the model, and the trained model is used for the comprehensive evaluation of enterprise investment decision-making performance [23–25].

6. Empirical Analysis

A company is a large modern coal chemical company that produces metallurgical coke and a variety of coal chemical products. By combining the scope of data provided by the industry and the analysis of time series investment indicators of the coking industry, the benchmarking method was applied, and the experts' judgement analysis of the energy and coal chemical industry was used to obtain the return on investment, the growth rate of the value of contribution of knowledge and intellectual assets, the R&D (research and development) cost rate, the production and sales rate of new products, the relative market share, the staff retention rate (employee satisfaction), the product production cycle efficiency, and the product (A,…, A9 in order). After eliminating the irregular index data items, the BP neural network model was trained by using the data of 10 items of relevant indexes and their fuzzy comprehensive evaluation results in 2000 in the coking industry (Table 1) [26], with a convergence accuracy of 0.001. The fuzzy evaluation and the neural network were validated against each other, the results were more satisfactory and improved the processing effect of the samples before model training compared with the single method, and the types of actual output, ideal output, and performance are shown in Table 2.

Indicators at the level of technological innovation are as follows: the total investment rate in intangible assets, return on investment in innovative products, R&D expenditure rate, rate of innovative products, rate of sales of innovative products, share of employees in R&D activities in the enterprise, labour productivity of new products, market share of new products, growth rate of sales revenue of new products, ratio of sales revenue of new products to total sales revenue, market volume of new products, growth rate of R&D expenditure, ratio of R&D expenditure to enterprise ratio of R&D expenses to enterprise sales revenue, ratio of R&D expenses to enterprise net profit, new product R&D expense rate, cost reduction R&D efficiency rate [27], product quality R&D efficiency rate, new product value added as a proportion of total product value added, reduction in production cost due to adoption of new technology, product innovation cycle, product quality R&D efficiency rate, new product contribution rate, new product R&D expense rate, speed of new product development, new product development, new product development capacity, and product quality research and development cost rate, as shown in Figure 2.

As shown in Figure 3, the different customer clusters can be analysed to know the customer level indicators. Customers include internal customers and external customers of the enterprise; external customers are commonly referred to as customers, and internal customers are referred to as internal employees. The ultimate goal is to satisfy external customers, and external customer satisfaction is closely related to internal customer satisfaction, which is the basis for external customer satisfaction, which in turn will lead to increased internal customer satisfaction. Internal customer indicators are as follows: staff retention rate (staff satisfaction), staff labour efficiency, total labour productivity, staff turnover rate, talent development growth rate, staff opinion adoption rate, staff training cost, staff knowledge, staff competence, and staff suggestion ability. External customer (commonly referred to as "recipients of products and services") indicators are market share, customer retention, customer profitability, customer acquisition, on-time product delivery, increase/decrease in sales from existing customers, repair rate, return rate, and length of time to resolve customer complaints.

7. Conclusions

An enterprise management index system based on neural network and fuzzy decision analysis is designed, and the multidependent decision-making problem in enterprise performance evaluation is solved by using triangular fuzzy theory. Finally, taking enterprise performance evaluation as an example, the effectiveness of this method is verified, in terms of social investment and donation rate, waste recovery rate, product energy intensity, success rate in dealing with environmental problems, public policy participation, pollution cost rate, average annual product life cycle cost, product raw material intensity, product service intensity, raw material recyclability, and product emission efficiency.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declared no conflicts of interest regarding this work.

References

[1] M. Khashei, S. R. Hejazi, and M. Bijari, "A new hybrid artificial neural networks and fuzzy regression model for time series forecasting," *Fuzzy Sets and Systems*, vol. 159, no. 7, pp. 769–786, 2008.

[2] X. Deyun, W. Zongjun, and C. Rongda, "Strategic performance measurement of investment decision-making based on fuzzy set and neural network," in *Proceedings. 2005 First International Conference on Neural Interface and Control, 2005*, pp. 163–166, Wuhan, China, 2005.

[3] R. J. Kuo, C. H. Chen, and Y. C. Hwang, "An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network," *Fuzzy Sets and Systems*, vol. 118, no. 1, pp. 21–45, 2001.

[4] L. Zhang, A. Yang, and W. Dai, "Investment decision-making based on fuzzy and artificial neural network," in *Third international conference on natural computation (ICNC 2007)*, vol. 3, pp. 297–300, Haikou, China, 2007.

[5] M. Khashei, M. Bijari, and G. A. R. Ardali, "Improvement of auto-regressive integrated moving average models using fuzzy logic and artificial neural networks (ANNs)," *Neurocomputing*, vol. 72, no. 4-6, pp. 956–967, 2009.

[6] C. Muriana, T. Piazza, and G. Vizzini, "An expert system for financial performance assessment of health care structures based on fuzzy sets and KPIs," *Knowledge-Based Systems*, vol. 97, pp. 1–10, 2016.

[7] K. K. Ang and C. Quek, "Stock trading using RSPOP: a novel rough set-based neuro-fuzzy approach," *IEEE Transactions on Neural Networks*, vol. 17, no. 5, pp. 1301–1315, 2006.

[8] R. J. Kuo, S. C. Chi, and S. S. Kao, "A decision support system for selecting convenience store location through integration of fuzzy AHP and artificial neural network," *Computers in Industry*, vol. 47, no. 2, pp. 199–214, 2002.

[9] D. Enke and N. Mehdiyev, "Stock market prediction using a combination of stepwise regression analysis, differential evolution-based fuzzy clustering, and a fuzzy inference neural network," *Intelligent Automation & Soft Computing*, vol. 19, no. 4, pp. 636–648, 2013.

[10] Z. Wang, N. Guo, S. Wang, and Y. Xu, "Prediction of highway asphalt pavement performance based on Markov chain and artificial neural network approach," *The Journal of Supercomputing*, vol. 77, no. 2, pp. 1354–1376, 2021.

[11] P. Singh, "Rainfall and financial forecasting using fuzzy time series and neural networks based model," *International Journal of Machine Learning and Cybernetics*, vol. 9, no. 3, pp. 491–506, 2018.

[12] B. Öztayşi, S. Çevik Onar, C. Kahraman, and A. Karaşan, "Fuzzy sets based performance evaluation of alternative wind energy systems," in *Energy Management—Collective and Computational Intelligence with Theory and Applications*, pp. 427–446, Springer, Cham, 2018.

[13] S. Asadi, E. Hadavandi, F. Mehmanpazir, and M. M. Nakhostin, "Hybridization of evolutionary Levenberg-Marquardt neural networks and data pre-processing for stock market prediction," *Knowledge-Based Systems*, vol. 35, pp. 245–258, 2012.

[14] J. Gao, "Performance evaluation of manufacturing collaborative logistics based on BP neural network and rough set," *Neural Computing and Applications*, vol. 33, no. 2, pp. 739–754, 2021.

[15] S. Bai, S. Li, R. Feng, and Y. Guo, "Organizational project selection based on fuzzy multi-index evaluation and bp neural network," in *2010 International Conference on Management and Service Science*, pp. 1–5, Wuhan, China, 2010.

[16] P. R. Kumar and V. Ravi, "Bankruptcy prediction in banks and firms via statistical and intelligent techniques - a review," *European Journal of Operational Research*, vol. 180, no. 1, pp. 1–28, 2007.

[17] T. G. Calderon and J. J. Cheh, "A roadmap for future neural networks research in auditing and risk assessment," *International Journal of Accounting Information Systems*, vol. 3, no. 4, pp. 203–236, 2002.

[18] M. Khashei and M. Bijari, "An artificial neural network (p, d, q) model for timeseries forecasting," *Expert Systems with applications*, vol. 37, no. 1, pp. 479–489, 2010.

[19] Z. Zheng-wan, W. Di, and Z. Chun-jiong, "Study of cellular traffic prediction based on multi-channel sparse LSTM," *Computer Science*, vol. 48, no. 6, pp. 296–300, 2021.

[20] P. An, Z. Wang, and C. Zhang, "Ensemble unsupervised autoencoders and Gaussian mixture model for cyberattack detection," *Information Processing & Management*, vol. 59, no. 2, article 102844, 2022.

[21] Y. C. Hu, "Incorporating a non-additive decision making method into multi-layer neural networks and its application to financial distress analysis," *Knowledge-Based Systems*, vol. 21, no. 5, pp. 383–390, 2008.

[22] W. Duan, J. Gu, M. Wen, G. Zhang, Y. Ji, and S. Mumtaz, "Emerging technologies for 5G-IoV networks: applications, trends and opportunities," *IEEE Network*, vol. 34, no. 5, pp. 283–289, 2020.

[23] X. Ning, P. Duan, W. Li, and S. Zhang, "Real-time 3D face alignment using an encoder-decoder network with an efficient deconvolution layer," *IEEE Signal Processing Letters*, vol. 27, pp. 1944–1948, 2020.

[24] X. Ning, W. Li, B. Tang, and H. He, "BULDP: biomimetic uncorrelated locality discriminant projection for feature extraction in face recognition," *IEEE Transactions on Image Processing*, vol. 27, no. 5, pp. 2575–2586, 2018.

[25] F. A. Al-Mekhlafi, R. A. Alajmi, Z. Almusawi et al., "A study of insect succession of forensic importance: dipteran flies (diptera) in two different habitats of small rodents in Riyadh City, Saudi Arabia," *Journal of King Saud University-Science*, vol. 32, no. 7, pp. 3111–3118, 2020.

[26] S. A. Bansode, V. R. More, S. P. Zambare, and M. Fahd, "Effect of constant temperature (20 0C, 25 0C, 30 0C, 35 0C, 40 0C) on the development of the Calliphorid fly of forensic importance, Chrysomya megacephala (Fabricus, 1794)," *Journal of Entomology and Zoology Studies*, vol. 4, no. 3, pp. 193–197, 2016.

[27] M. Tkáč and R. Verner, "Artificial neural networks in business: two decades of research," *Applied Soft Computing*, vol. 38, pp. 788–804, 2016.