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# Utilizing Enterprise Economic Benefit Evaluation Methods in Edge Intelligent Neural Network Applications

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## ABSTRACT

The core of enterprise economic benefit evaluation lies in the development of a quantitative identification model. The Back Propagation (BP) neural network possesses robust parallel computing, adaptive learning, and error correction capabilities, which can effectively reveal the economic benefits of enterprises and their relationship with influencing factors. This study establishes an economic benefit evaluation model for express delivery enterprises based on the BP neural network. The model takes the annual profit rate of enterprises as the quantitative index of economic benefits and selects 13 factors, both external and internal, influencing the annual profit rate of express delivery enterprises as inputs for the BP neural network model. The economic benefit evaluation model based on BP neural network meets the requirement of objective mean square error in the 300th training cycle. The research results demonstrate that the BP model significantly saves computing time and enables rapid, comprehensive, and objective evaluation of the economic benefits of industrial enterprises.

## KEYWORDS

Neural networks, Environmental impact, Economic benefits, Multimodal ML modelling, Edge mobile computing

The advent of the Internet of everything (IoE) era has brought about a plethora of novel applications, such as smart cities, autonomous vehicles, and edge computing, fundamentally reshaping the way businesses operate and engage with their environment (Farias da Costa et al., 2021). Express delivery enterprises, at the forefront of this technological revolution, face a unique set of challenges in evaluating and optimizing their economic benefits. Simultaneously, the constraints imposed by edge computing devices, characterized by limited computational and storage resources, present a formidable obstacle to the direct deployment of complex analytical models on these platforms. This necessitates the development of tailored, efficient evaluation methods that cater to the specific needs of express delivery firms operating in the IoE era, considering both the idiosyncrasies of their business models and the technological limitations of edge computing.

Express delivery enterprises, with their inherently dynamic operations and reliance on real-time data processing, grapple with several distinct challenges in economic benefit evaluation. These include the imperative to rapidly adapt to shifting market conditions, effectively manage a diverse and geographically dispersed asset base, and optimize resource utilization amid fierce competition. Traditional evaluation methods, such as the balanced scorecard, analytic hierarchy process (AHP), and

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fuzzy evaluation techniques, have been employed across various industries to assess economic benefits (Singh et al., 2018). However, these approaches often suffer from subjectivity in criteria weighting and may struggle to capture the nonlinear, interdependent relationships between multiple internal and external factors that significantly influence the economic performance of express delivery firms.

Moreover, these conventional methods typically neglect the environmental impact from external industries, a consideration gaining increasing importance in corporate decision-making as sustainability concerns rise to the fore. Consequently, there is a growing awareness of the limitations of these tools in providing a comprehensive and accurate assessment of economic benefits for express delivery enterprises operating in the IoE era.

Neural networks, particularly the back propagation (BP) algorithm, offer a promising solution to the challenges inherent in traditional evaluation methods (Wright et al., 2022). Their inherent strengths in parallel computation, adaptive learning, and error correction enable them to effectively model complex, non-linear relationships between economic benefits and their multitude of influencing factors. Moreover, neural networks' capacity to extract knowledge from historical datasets and extrapolate this learning to novel contexts ensures they are adept at accommodating the ever-changing dynamics intrinsic to express delivery operations.

In the context of edge computing, neural networks can potentially mitigate computational constraints by leveraging their inherent parallelism and ability to operate with reduced complexity. Implementing lightweight, optimized neural network architectures or utilizing techniques like model compression and transfer learning can facilitate the deployment of neural network-based evaluation models directly on edge devices, enabling real-time, localized decision-making without the reliance on a centralized cloud infrastructure. This not only reduces latency and improves responsiveness, but also safeguards data privacy and minimizes communication costs, both critical considerations in the express delivery industry.

Edge computing, as a distributed computing paradigm, brings computation and data storage closer to the point of data generation, thereby reducing latency and bandwidth requirements. For express delivery enterprises, this translates into expedited processing of large volumes of real-time data generated by Internet of things (IoT) devices, sensors, and other edge-enabled technologies. By facilitating the execution of complex analytics tasks, such as economic benefit evaluation using neural networks, at the edge, companies can swiftly adapt to changing market dynamics, optimize resource allocation, and enhance overall operational efficiency.

In summary, the introduction of advanced neural network techniques in the realm of enterprise economic benefit evaluation holds substantial promise for overcoming the limitations of traditional methods and harnessing the full potential of edge computing in the express delivery industry. This study aims to contribute to this evolving field by developing and validating a BPNN-based economic benefit evaluation model tailored specifically to the needs and constraints of express delivery enterprises operating in the IoE era.

## LITERATURE REVIEW

The evaluation of enterprise economic benefits, particularly in the context of edge intelligent neural network applications, has been a subject of considerable research interest in recent years. This section presents a synthesis of key studies that contribute to the understanding and development of effective evaluation methodologies for this domain.

Edge intelligent neural networks represent a convergence of two transformative technologies: artificial neural networks (ANNs) and edge computing. ANNs, inspired by the structure and functionality of biological nervous systems, are designed to learn patterns in data through interconnected layers of artificial neurons. These networks excel in tasks requiring nonlinear relationship extraction, pattern recognition, and prediction. When combined with edge computing, which pushes computation, data storage, and analysis more closely to the source of data generation, ANNs can operate in resource-constrained environments, offering real-time responses and improved data privacy due to reduced reliance on centralized cloud infrastructure (Wang et al., 2023). Edge intelligent neural networks have found applications in various domains, including industrial automation, smart transportation, and healthcare. They enable on-site decision-making, anomaly detection, and predictive maintenance by processing data from IoT devices, sensors, and other edge-enabled technologies. Furthermore, they facilitate the deployment of computationally intensive models, such as deep neural networks (DNNs), on edge devices, allowing for low-latency inference and immediate action (C. Zhang & Lu, 2021).

Several studies have demonstrated the utility of neural networks in capturing the intricate relationships between various factors influencing enterprise profitability and their subsequent impact on economic benefits. For instance, Jin et al. (2021) employed back propagated neural networks (BPNNs) for the cost-benefit analysis of investment projects, revealing the potential of these models to accurately quantify financial outcomes in complex decision-making scenarios. Similarly, X. Zhang et al. (2023) developed a BPNN-based comprehensive evaluation system for coal seam impact risks, showcasing the ability of neural networks to assess risk levels and inform strategic planning. Focusing specifically on the express delivery industry, Zhou et al. (2023) utilized big data and neural networks to enhance the economic benefit evaluation system for Chinese enterprises, promoting sustainable production practices. Their approach underscores the importance of integrating real-world data and advanced analytics to derive actionable insights for business improvement.

The advent of edge computing has opened up new possibilities for the efficient deployment of neural network models in resource-constrained environments. Researchers have investigated ways to optimize neural network architectures and training processes for edge devices, ensuring both computational efficiency and model accuracy. For example, Ismaeel et al. (2023) explored the use of deep recurrent neural networks (RNNs) for traffic pattern classification in smart cities, demonstrating how edge-compliant neural network models can effectively handle temporal data and enable responsive traffic management. In the realm of human capital management, Khang et al. (2023) advocated for data-driven approaches leveraging big data, databases, and data mining techniques to optimize workforce management systems in the Industry 4.0 context. Their work highlights the potential of edge computing to facilitate real-time processing and decision-making based on locally generated data, thus enhancing organizational agility and productivity.

Enterprise economic benefit evaluation is a vital process for assessing the financial consequences of business decisions, investments, and operations. Traditional methods often rely on financial ratios, cost-benefit analyses, and discounted cash flow techniques. However, the complexity and dynamism of today's business environments, exacerbated by the proliferation of data-driven technologies and the IoE, call for more sophisticated evaluation frameworks. Neural network-based approaches have emerged as promising alternatives for enterprise economic benefit evaluation. Their ability to model nonlinear relationships, handle high-dimensional data, and learn from historical patterns makes them well-suited for capturing the intricate interplay between various internal and external factors affecting enterprise profitability. BPNNs, for instance, have been widely applied in this context due to their parallel processing, adaptive learning, and error correction capabilities (Liu et al., 2023). Recent studies have demonstrated the effectiveness of neural networks in evaluating economic benefits across different industries. In the express delivery sector, K. Zhang et al. (2022) developed a BPNN-based model to quantify the impact of operational factors on enterprise profit rates, while Li et al. (2024) utilized RNNs to predict demand fluctuations and optimize resource allocation. These examples illustrate the potential of neural networks to provide accurate, data-driven insights for informed decision-making.

Research on edge intelligent neural networks and their application to enterprise economic benefit evaluation continues to evolve, driven by advances in hardware, algorithmic innovations, and the increasing adoption of IoE technologies. The miniaturization of processing units, increased energy efficiency, and specialized hardware (e.g., neuromorphic chips) are enabling the deployment of more complex neural network architectures on edge devices, enhancing their computational capabilities and reducing latency (Choi et al., 2020). Techniques such as pruning, quantization, and knowledge distillation are being employed to compress and optimize neural network models, making them more suitable for resource-limited edge environments without sacrificing accuracy (Liang et al., 2021). Researchers are investigating the integration of multiple data sources (e.g., visual, audio, and text) in neural network models for more holistic economic benefit evaluations. Multi-modal learning can capture complementary information from different data types, improving model robustness and predictive power (Craig et al., 2021). To address privacy concerns and reduce data transmission costs, edge-federated learning paradigms are being explored, where neural network models are trained collaboratively on decentralized data stored at the edge, without direct data exchange (Xu et al., 2021). This approach preserves data privacy while harnessing the collective wisdom of multiple edge devices for improved model performance.

Recognizing the synergistic potential of neural networks and edge computing, scholars have sought to combine these technologies for enhanced economic benefit evaluation. Bourechak et al. (2023) conducted a comprehensive review of the intersection between artificial intelligence (AI) and edge computing in IoT-based applications, emphasizing the promise of AI-driven decision-making and data processing at the edge for industries like express delivery services. Their findings support the notion that edge-enabled neural networks can significantly improve responsiveness and operational efficiency. Dyczko (2023) further demonstrated the applicability of neural networks in real-time forecasting and urban competitiveness assessment, showcasing the value of these models in informing decision-making and driving resource optimization. The former study employed neural networks for the prediction of key coking coal quality parameters, while the latter used cloud computing and neural networks to assess urban competitiveness.

In summary, the related work illustrates a rich landscape of research that combines neural networks and edge computing technologies to address the complexities of enterprise economic benefit evaluation in the dynamic IoE landscape. These studies emphasize the adaptability, accuracy, and computational efficiency of tailored neural network models, which make them valuable tools for rapid, comprehensive, and objective assessments in the context of express delivery firms. The seamless integration of advanced neural network techniques with edge computing infrastructure allows for the effective processing of vast, real-time data generated by IoT devices, empowering businesses to make informed, data-driven decisions that ultimately boost their operational efficiency and competitiveness.

## MATERIALS AND METHODS

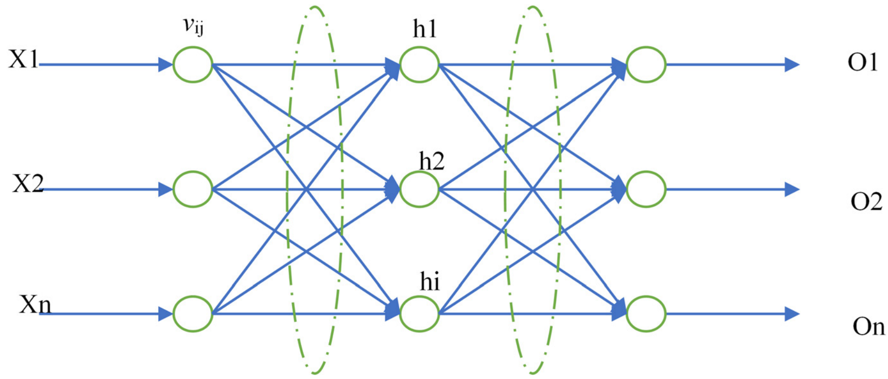
ANNs refer to a network system that simulates the structure and function of the human brain; they use a large number of processing components and are established manually (Song & Wang, 2023). Since the inception of the first neural network model, the McCulloch-Pitts model in 1943, researchers have embarked on utilizing logical and mathematical methodologies to analyze how neural networks represent and interact with real-world phenomena. This endeavor has equipped Artificial Neural Networks (ANNs) with the capability to learn from data, adapting their internal structures to better apprehend and predict complex relationships within the information they encounter. ANNs have become a powerful tool to solve many practical problems due to their characteristics of large-scale parallel processing, fault tolerance, self-organization, self-adaptive ability, and strong association function (Kar et al., 2023).

A multi-layer ANN model can be described in this way:

1. The network consists of an input layer, $N$ ($N$>1) hidden layers, and an output layer.
2. The $k^{th}$ layer contains $N_k$ neurons.
3. The weight table from the $i$-th neuron in the $k$-1 layer to the j-th neuron in the $k$-th layer is $w_i^{jk-1,k}$.

BP network refers to a multi-layer feedforward neural network. The transfer function of its neurons is a sigmoid function, and the output is a continuous quantity between 0 and 1. It can realize any

Figure 1. BPNN with a single hidden layer structure




nonlinear mapping from input to output layers. The BP learning algorithm requires that the transfer function of the neuron model is a bounded continuous differentiable function (Kou et al., 2023). A network composed of neurons with such a transfer function can be learned by a continuous hypersurface (rather than just a hyperplane). In the case of complex input sample space, three layers of an input layer, a hidden layer, and an output layer are used, and each layer is fully connected. At this time, the learned network can form a conforming surface with *n*-1 hypersurfaces. Complex classification tasks make up for the shortcomings of any single-layer perceptrons (Aminizadeh et al., 2023). The BPNN structure eliminates errors through error BP. During training, the generalized error of the output layer unit is solved by calculating the error between the output and expected values, and then the error is back-propagated to help find the generalized error of the hidden layer unit. Then, the output and hidden layers are adjusted until the system error is acceptable. Furthermore, the weights between the input layers and thresholds of the hidden and output layers will not change. The structure of the three-layer feedforward BPNN is shown in Figure 1.

It has been proved that the BPNN with a hidden layer can process any function in the closed interval, so a BPNN with a three-layer structure can complete the discrete mapping from *N* dimension space to *M* dimension space. Therefore, the BPNN usually adopts a single hidden network layer.

## Data Preprocessing

Before constructing the BPNN model, the collected data underwent a series of preprocessing steps to ensure consistency, completeness, and suitability for effective neural network training.

### *Normalization*

All numeric data representing the 13 influencing factors and the annual profit rate were normalized using min-max scaling. This transformation rescaled each variable to a range between 0 and 1, effectively reducing the influence of variable scales and enhancing the comparability of input features. Min-max normalization was performed according to Eq. (1):

$$\chi_{norm} = \frac{\chi - \chi_{min}}{\chi_{max} - \chi_{min}} \tag{1}$$

where $\chi$ is the original value, $\chi_{min}$ is the minimum value of the variable in the dataset, and $\chi_{max}$ is the maximum value of the variable. Normalization helped to mitigate the effects of outliers and ensure that the learning process was not unduly influenced by variables with inherently larger numerical ranges.

### Missing Value Handling

Any missing data points in the acquired financial reports were addressed through imputation strategies. Mean imputation was employed for continuous variables, replacing missing values with the average value of the respective variable across all available observations. For categorical variables, missing entries were filled using mode imputation, substituting the most frequently occurring category within the dataset. These methods were chosen to minimize distortion of the data distribution while preserving the overall structure and relationships among variables.

### Data Transparency

Enhancing data transparency in a study is crucial for ensuring that the findings can be understood, replicated, and trusted by other researchers and stakeholders. In the context of the study exploring the use of a BPNN-based economic benefit evaluation model for express delivery enterprises in the IoE era, transparency is achieved through a clear description of data sources, collection methods, and analysis techniques:

1. Data sources. Top 40 logistics companies: The study draws upon data from the top 40 logistics companies, selected because they represent leading players in the express delivery industry. These companies are likely to operate under diverse market conditions, exhibit a range of economic performances, and thus serve as a representative sample of the target population. This choice ensures that the model is exposed to a wide variety of influential factors affecting economic benefits, enhancing its generalizability to other enterprises in the sector.
2. Data collection methods. Quantitative data acquisition: Specific financial and operational metrics are collected for each of the 40 logistics companies. These might include revenue, expenses, profit margins, asset utilization rates, service quality indicators, customer satisfaction scores, delivery times, and other relevant performance measures. Data may be gathered from publicly available financial reports, company disclosures, or industry databases or through direct communication with the companies themselves, ensuring access to accurate and up-to-date information.

### Contextual Information

In addition to numerical data, contextual factors that influence economic benefits are also collected. These could encompass market trends, competitive landscapes, regulatory changes, technological advancements, and environmental impacts specific to the express delivery sector. This information is obtained through a combination of desk research, expert interviews, industry reports, and news articles to provide a comprehensive understanding of the broader context in which these companies operate:

3. Analysis techniques. BPNN model development: The study employs a BPNN, a type of ANN known for its ability to learn nonlinear relationships and patterns in data. The BPNN is tailored specifically to the needs and constraints of express delivery enterprises operating in the IoE era, taking into account the unique characteristics of their business models and the technological limitations of edge computing.

### Input-Output Configuration

The model is configured with appropriate input variables derived from the collected data, such as operational metrics and contextual factors, to represent the multifaceted nature of economic benefits in the express delivery context. The output variable(s) correspond to specific economic performance indicators, such as profit rates or return on investment, which the model aims to predict or analyze.

### *Hyperparameter Tuning*

A systematic grid search is performed to determine the optimal number of hidden neurons in the BPNN. This process involves evaluating the model's performance across a range of complexities using a 10-fold cross-validation scheme. Key performance metrics like mean squared error (MSE), accuracy, and $R^2$ are calculated for each fold, and the configuration with the lowest average MSE (or highest $R^2$, depending on the chosen evaluation criterion) is selected as the optimal architecture. This approach ensures a robust and replicable framework for assessing the model's generalization capabilities and mitigates the risks of underfitting or overfitting.

### *Training and Testing*

The dataset is divided into training and testing sets, with 30 enterprises allocated for training and 10 for testing. This partitioning strategy is based on considerations of statistical power, representativeness, and the practical limitations of the study context, particularly regarding resource-constrained edge devices. The relatively small sample size allows for efficient model convergence, effective pattern learning, and manageable computational demands.

### *Model Performance Assessment*

The trained network's performance is evaluated using the 10-fold cross-validation scheme, with average MSE, accuracy, and $R^2$ computed across all folds. These metrics provide a transparent and objective assessment of the model's predictive accuracy and goodness-of-fit, contributing to the credibility of the results.

## Influencing Factors Selection

The choice of 13 influencing factors was guided by theoretical considerations and empirical evidence from the literature on factors known to significantly impact the economic performance of logistics companies. These factors encompassed both external market conditions and internal operational characteristics, ensuring a comprehensive evaluation of the enterprises under scrutiny. Specifically, they were selected based on:

1. Relevance: Each factor was deemed directly or indirectly relevant to the economic benefit of express delivery enterprises, reflecting aspects of their business environment or internal management that could plausibly affect profitability.
2. Availability: Data for all selected factors were reliably obtainable from the annual financial reports of the top 40 logistics companies, ensuring the feasibility of the study and the validity of subsequent analyses.
3. Discriminatory Power: The factors were expected to exhibit sufficient discriminatory power, meaning they should be able to distinguish between companies with varying levels of economic performance and contribute to the model's ability to accurately predict profit rates.

## BPNN Architecture

The designed BPNN model consisted of three layers: an input layer, a hidden layer, and an output layer. The input layer had 13 nodes corresponding to the 13 selected influencing factors. The hidden layer comprised a number of neurons determined through trial-and-error experimentation and validation, ensuring a balance between model complexity and generalization capacity. The optimal number of hidden neurons was arrived at by considering the trade-off between underfitting (insufficient representation capacity) and overfitting (excessive complexity), with the final choice minimizing the MSE on a validation set and ensuring acceptable training times.

The output layer contained a single node, representing the predicted annual profit rate of the enterprise. The sigmoid activation function was employed in the hidden layer to introduce non-linearity into the model, allowing it to capture complex relationships between the input factors and the economic benefit. The linear activation function was used in the output layer to produce a continuous profit rate estimate within the normalized range.

## Feature Selection and Optimization Algorithm

No explicit feature selection techniques were applied in this study, as the initial selection of 13 influencing factors was already guided by their theoretical relevance and empirical importance. All chosen factors were deemed essential for understanding the economic dynamics of express delivery enterprises and were thus retained in the model.

The optimization algorithm used during the training phase was the resilient Backpropagation (Rprop) algorithm. Rprop was preferred due to its ability to efficiently handle non-smooth error surfaces, which are common in neural network training, and its robustness against oscillations and local minima. It adjusts the weights based on the sign of the gradient rather than its magnitude, allowing for faster convergence and improved stability compared to traditional gradient descent methods.

## Cross-Validation Procedure and Hidden Neuron Optimization

To evaluate the proposed BPNN model's robustness and generalization capability, we employed a 10-fold cross-validation strategy. This choice of “k = 10” balances computational efficiency with performance estimation variance reduction, aligning with widely accepted conventions. The dataset, comprising annual financial data from the top 40 logistics companies, was randomly divided into 10 equally sized subsets (folds). Each fold served as the test set once, with the remaining nine forming the training set. This process was iterated 10 times, ensuring every observation was part of the test set once and evaluating all possible combinations of training and validation sets. Performance metrics—such as MSE, accuracy, and coefficient of determination ($R^2$)—were computed across all folds, providing an unbiased estimate of the model's predictive power on unseen data and mitigating overfitting risks.

Determining the optimal number of hidden neurons in the BPNN involved a systematic grid search combined with cross-validation. A predefined range of candidate values for the number of hidden neurons spanned from a minimum of five to half the sum of input and output nodes, covering a wide spectrum of model complexities. For each candidate value, the following procedure was executed:

1. Initialization: The BPNN was initialized with the specified number of hidden neurons.
2. Training: The network was trained using the resilient BP (Rprop) algorithm, which was chosen for its efficacy in handling non-smooth error surfaces and resilience against oscillations and local minima. The Rprop algorithm adjusted the weights based on the sign of the gradient, facilitating faster convergence and improved stability compared to traditional gradient descent methods.
3. Validation: The performance of the trained network was assessed using the 10-fold cross-validation scheme described above, with the average MSE, accuracy, and $R^2$ computed across all folds.
4. Selection: The configuration with the lowest average MSE (or highest $R^2$, depending on the specific evaluation criterion chosen) was identified as the optimal number of hidden neurons.

This systematic exploration of the hyperparameter space allowed for an objective evaluation of the model's performance across a range of complexities. The chosen optimal number of hidden neurons not only minimized the MSE on the validation set, but also ensured acceptable training times, striking a balance between underfitting (insufficient representation capacity) and overfitting (excessive complexity).

### Sample Size Rationale

The decision to utilize 30 enterprises for training and 10 for testing in the BPNN model was guided by considerations related to statistical power, representativeness, and practical limitations. Selecting 30 training samples aims to balance model complexity, training time, and effective pattern learning. Even with a small sample size, the BPNN can converge to an optimal solution without being overly sensitive to noise or overfitting. A sample size of 30 is deemed adequate for simpler architectures to capture essential relationships between input factors and the target variable, provided the relationships are not overly intricate and the data is not highly variable. Additionally, this size allows for a manageable computational load, especially important for resource-constrained edge devices, a key concern in this study.

The choice of the top 40 logistics companies as the data source aimed to ensure representativeness of the target population of express delivery enterprises. These companies are likely industry leaders, operating under diverse market conditions and exhibiting various economic performances, enhancing the model's generalizability. By including 75% of these top companies in the training set, the model is exposed to a wide array of influential factors and their effects on economic benefits. This diverse training data contributes to capturing essential patterns and generalizing well to other express delivery enterprises, though exact representativeness cannot be quantitatively assessed without information on the total population size and characteristics.

While the sample comprises industry leaders, certain biases may be introduced. Firstly, focusing solely on the top 40 firms may bias the model toward understanding larger, more successful, and potentially more resourceful enterprises, potentially limiting its applicability to smaller or less-established companies. Secondly, selecting enterprises based solely on ranking may overlook regional variations, market niches, or unique operational strategies affecting economic benefits differently. Lastly, the absence of a formal sampling framework, such as random or stratified sampling, raises concerns about potential selection bias, though using a top-ranking list can be seen as a form of convenience sampling that captures a sector's leading performers pragmatically.

## RESULTS AND ANALYSIS

### Index Selection

An enterprise is an economic organization for profit. From the perspective of operation mode, the enterprise is an input-output system. By investing capital, humans, and other resources, the enterprise uses methods such as adjusting and coordinating the organization to finally reap economic benefits. Generally, the economic benefits of an enterprise are reflected through five dimensions: market value, profitability, solvency, operating capacity, and growth capacity (Hu, 2023). This study selects the annual profit rate of enterprises as a quantitative indicator to replace the economic benefits of enterprises and selects three external influencing factors and 10 internal influencing factors to analyze the economic benefits of enterprises from two aspects of the external market environment and their own operating conditions, as seen in Table 1. The internal influencing factors are denoted as $N_1$, $N_2$, ... $N_{10}$; the external influencing factors are denoted as $W_1$, $W_2$ and $W_3$, respectively. From the perspective of the external environment, the annual profit rate of a company will be affected by the "background effect" of the industry environment in which it operates. Therefore, this study starts from the industry environment where the company is located and selects market concentration, market competition, and industry prosperity indexes as the external factors affecting the company's annual profit rate.

1. Market concentration. Market concentration is a fundamental measure of market structure, indicating the percentage of a specific indicator (such as sales volume) held by a few enterprises within an industry. Common indicators include the industry concentration ratio (CRn), Herfindahl-Hirschman Index (HHI), Lorentz curve, Gini coefficient, inverse index, and entropy index. It

reflects the extent to which production factors in an industry are controlled by a limited number of large enterprises, indicating the level of monopoly in the industry. Factors contributing to high market concentration include limited company entry in emerging or immature markets and barriers to entry, such as administrative measures, technical barriers, or economies of scale, resulting in market monopolies by a few enterprises.

2. Market competition. Market competition mainly comes from the drive of interest subjects in the market to their own material interests and the fear of losing material interests due to being eliminated by the market. Moderate market competition is conducive to the technological innovation and profit growth of enterprises and the technological upgrading of the entire industry. For example, the rise of Internet finance and the competition and impact on the traditional banking industry have led to the accelerated process of technological innovation and product iteration in the banking industry (Reddy, 2023). However, for a monopolistic market, monopoly enterprises have insufficient motivation to improve the product quality due to the high degree of convenience in obtaining profits.
3. Industry prosperity. Industry prosperity is an indicator used to reflect the state or development trend of a particular survey group or a social and economic phenomenon. From the perspective of the company's internal operating conditions, this study selects parameters such as the capital intensity, R&D investment, compensation structure, enterprise value, operating leverage, price-earnings (P/E) ratio, debt level, and entry barriers (Luo et al., 2023). The 10 influencing factors of enterprise age and enterprise scale are regarded as the internal influencing factors of enterprise economic benefits.
4. Capital intensity. Capital intensity is the degree of investments in various capitals of an enterprise. Compared with labor-intensive enterprises, capital-intensive enterprises have more advanced production equipments, employ fewer employees, and have stronger labor skills and higher work efficiency. The advanced level of production equipments and the technical levels of employees are all important factors that affect corporate profits (Zkik et al., 2023).
5. R&D investment. This study uses the proportion of enterprise R&D expenses in the total operating cost of the enterprise to reflect the R&D investment of enterprise. R&D investment mainly affects the profit level of enterprises from three aspects. First, effective R&D projects can bring new technologies or new products, enhance the competitiveness and profitability of enterprises, and promote the profit level of enterprises. Second, as a component of corporate costs, R&D investment has a negative impact on corporate profit margins. Third, R&D investment helps companies to deduct part of their taxes, which positively boosts corporate profits.
6. Salary structure. This study uses the ratio of the top three managers' salaries to the total salary of all employees of the company to measure the company's salary structure and then reflects the influence of managers in operations. Corporate executives are more motivated to carry out operation and management to pursue higher corporate profits, which helps to improve corporate profitability. Therefore, when designing the salary structure, it should obey the major premise that the salary system achieves the goal. The salary system has two main purposes: first, to ensure that the enterprise reasonably controls costs and second, to help the enterprise effectively motivate employees.
7. Enterprise market value. The market value of a company is an effective way to measure the size and economic benefits of a company's assets, and it is a more intuitive reflection of the company's profitability by the market. This study uses the product of the number of shares issued by the company and the company's current share price to represent the company's market value.
8. Operating leverage. Operating leverage is used to indicate the extent to which the firm's economic benefits are affected by the existence of fixed costs in the firm's total cost. According to the cost behavior, within a certain range of production and sales, the increase of production and sales will not affect the total fixed cost but will reduce the fixed cost per unit product, thus improving the profit per unit product and making the profit growth rate greater than the growth rate of

**Table 1. Selection of factors affecting the economic benefits of enterprises**

| | | |
|---|---|---|
| External influencing factors | Market concentration | *W*i |
| | Market competition | *W*2 |
| | Industry prosperity | *W*3 |
| Internal influencing factors | Capital intensity | *N*i |
| | R&D investment | *N*2 |
| | Salary structure | *N*3 |
| | Enterprise market value | *N*4 |
| | Operating leverage | *N*5 |
| | P/E ratio | *N*6 |
| | Debt level | *N*7 |
| | Barriers to entry | *N*8 |
| | Enterprise age | *N*9 |
| | Enterprise size | *N*i0 |

production and sales. On the contrary, the decrease of production and sales volume will increase the fixed cost per unit product, thus reducing the profit per unit product and making the profit decline rate greater than the decline rate of production and sales volume.

9. P/E ratio. The P/E ratio, also known as the stock P/E ratio, reflects the level of the stock price of the listed company or the level of the stock market value by combining the stock price with the operating profit of a company. This study uses the ratio of the company's current stock price per share to earnings per share, that is, the company's "market price per 1 yuan of after-tax profit," to represent the company's P/E ratio.
10. Debt level. Debt level is used to reflect the ability of an enterprise to use the amount of debt to carry out business activities and is an indicator to judge the economic benefit and profitability of an enterprise. Although a higher level of corporate debt will bring greater financial risks to the company, it will also provide the company with sufficient operating funds. In addition, when the debt level of the enterprise is too low, the stability of the enterprise funds is better, but the business activities of the enterprise may be affected by insufficient cash flows.
11. Barriers to entry. The entry barrier is an indicator to study the difficulty of potential competitors to enter a specific market and to predict the degree of competition and market performance in the market. From the perspective of corporate behavior, existing companies in the industry mainly cultivate customer loyalty in the market and form economies of scale through a large number of advertising costs, market resources and channel construction costs, large-scale production equipments, and necessary capital investments.
12. Enterprise age. Enterprise age measures the existence time of the enterprise, which is mainly reflected in the use time of enterprise equipments, the age distribution of employees, enterprise culture, and business experiences. These are closely related to the production efficiency, management level, operation efficiency, and R&D capability of the enterprise, thus affecting the economic benefit level of the enterprise.
13. Enterprise size. The size of the enterprise has a double impact on the economic efficiency of the enterprise. Specifically, when the relative added value of output is greater than the relative added value of various production factors, expanding the scale of the enterprise will improve production efficiency, thereby promoting the increase of enterprise profits; the emergence of problems such as inefficiency, which will in turn adversely affects the corporate profits.

## Model Establishment and Data Sources

The principle of establishing the model for the evaluation and assessment of enterprise economic benefits is that the performance indicators of all aspects of the evaluated enterprise economic benefits are taken as the input vector of the BP network model, and the evaluation results are taken as the output of the model. Enough successful evaluation samples are used to train the network, so that the network can remember the weight of each index, the performance of the enterprise, and the quality of completion, etc. A well-trained neural network model can get the evaluation results by inputting the vector indicators of the evaluated enterprise.

The enterprise economic benefit evaluation model based on the BPNN established in this study includes 13 input layer nodes and one output layer node. How to select the correct number of hidden neurons is a complex problem. If the number of neurons is not enough, the network cannot run. However, if there are too many samples, the research cycle will be longer, so that the network will become fragile, the performance will decline, it will be impossible to judge which samples are not received, and the error tolerance will be low. Therefore, the number of neurons with hidden layers is required to be just right. Based on this, this study uses the step-by-step growth method; that is, it starts from a simple network, by gradually trying to increase the number of neurons in the hidden layer to determine the number of hidden layer nodes when the MSE is the smallest, so as to determine the hidden layer. When the number of nodes is seven, it is most suitable. The BPNN structure of the enterprise economic benefit evaluation model is finally determined as: a 13-7-1 structure, which includes 13 input layer nodes, seven hidden layer nodes, and one output layer node.

The indicator system includes some quantitative and qualitative indicators that can reflect the performance. The quantitative indicators are different in size, dimension, and change trend, while the qualitative indicators are difficult to compare. In order to make each indicator comparable in the whole system, they should be treated as quantitative and qualitative indicators with the same tendency and dimensionless and located in the closed intervals [0,1]. The rapid growth of China's logistics industry shows that with the economic development, the demand for logistics also increases. However, the high cost of logistics still restricts the development of the logistics industry, which is also a major bottleneck for the operation of the national economy. Therefore, improving the performance of local logistics enterprises is of great practical significance for promoting the development of the logistics industry and improving the competitiveness of the logistics enterprises in the international market.

This study takes the logistics industry as the research object to evaluate its economic benefits; the top 40 logistics companies are selected as the data collection objects, and the factors affecting the economic benefits of enterprises are combined. Based on the 2019 annual financial reports of these 40 companies in the Flush Database, the values of 13 influencing factors and their annual profit margins corresponding to 40 listed logistics companies were obtained. Moreover, in addition to the logistics industry used in this study, the economic benefits of other industries (such as the gold industry) can also be evaluated through the BPNN evaluation model established in this study. When evaluating the economic benefits of different industries, it is necessary to adjust the parameters and variable values of the established BPNN evaluation model.

## Model Training

The first 30 listed logistics companies in this study are used as the training samples to train the enterprise economic benefit evaluation model based on the BPNN, and the remaining 10 listed logistics companies are used as test samples to verify the enterprise economic benefit evaluation model. The training process of the enterprise economic benefit evaluation model based on BPNN is shown in Figure 2, and the initial parameter settings are shown in Table 2.

Figure 3 shows the training error diagram of the established enterprise economic benefit evaluation model based on the BPNN. It can be seen from Figure 2 that the enterprise economic benefit evaluation model reached the target MSE requirement in the 300th training cycle. In addition, the fit between the actual output value of the training set and the predicted output value is very high, reaching higher

**Table 2. Initial parameter values of BPNN**

| Parameter | Value |
|---|---|
| Learning rate | 0.08 |
| Maximum number of network training loops | 40000 |
| MSE | 0.20% |

than 99.00%. Therefore, it can be judged that the enterprise economic benefit evaluation model based on the BPNN trained in this research is a better enterprise economic benefit evaluation model.

## Model Verification

The ultimate goal of the BPNN training is to ensure that the trained enterprise economic benefit evaluation model has good generalization ability to non-training samples. That is, the enterprise economic benefit evaluation model based on the BPNN is not only a training sample. It has a good fitting ability and can effectively approximate the inherent laws of the samples. In order to further verify the generalization ability of the established BPNN-based enterprise economic benefit evaluation model, this study selects the remaining 10 logistics companies as test samples to test the trained BPNN model. In addition, the external factors that affect the annual profit rate of enterprises, namely market concentration, market competition, and industry prosperity index, have the same value in each logistics enterprise. Therefore, this study will evaluate the economic benefits of enterprises based on the BPNN. Two tests were carried out, namely adding external influencing factors and not adding external influencing factors, so as to analyze the degree of influence of external influencing factors on the results.

**Figure 2. Training process of evaluation model of enterprise economic benefit based on BPNN**

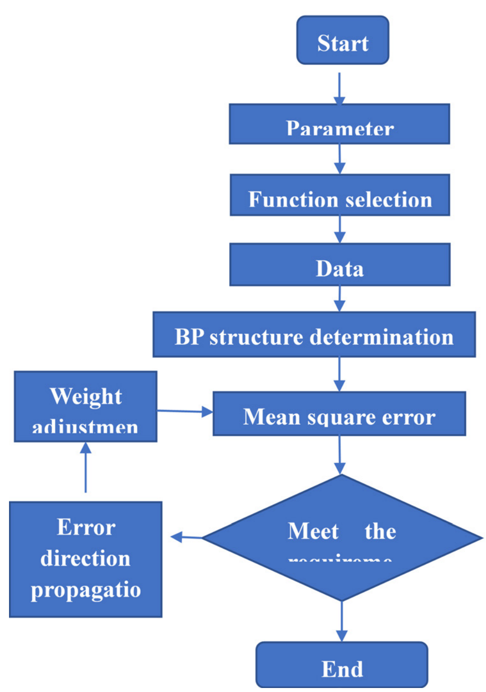


**Figure 3. Training errors of evaluation model of enterprise economic benefit based on BPNN**

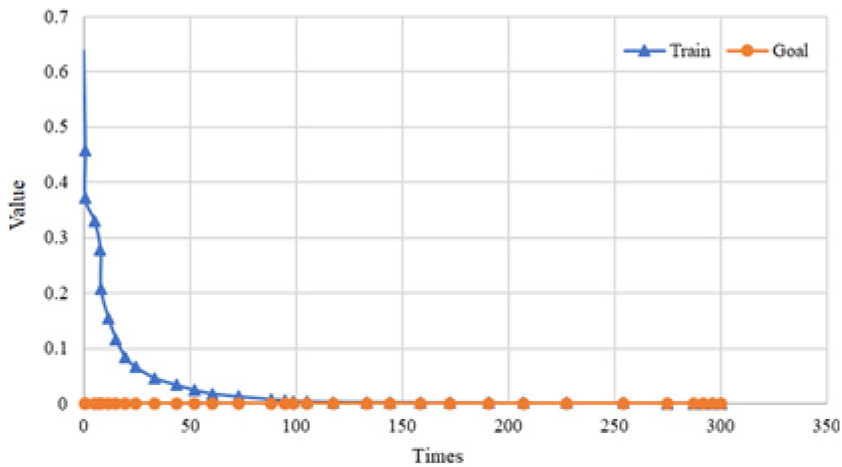



Figure 3 shows the test results of the enterprise economic benefit evaluation model based on the BPNN. It can be seen from Figure 3 that, compared with the relative error of each test sample without adding external influencing factors, the relative error value of each test sample after adding external influencing factors is smaller. In addition, the MSE of the prediction output of the enterprise economic benefit evaluation model after adding external influencing factors is less than 0.20%, which is significantly smaller than that of the enterprise economic benefit based on the BPNN established without external influencing factors. We evaluated the MSE of the model's predicted output results. This shows that the enterprise economic benefit evaluation model based on the BPNN established in this study has good generalization ability. Although, for all samples, the values of the external influencing factors (i.e., market concentration, market competition, and industry sentiment index) are the same. However, according to the test results with and without external influence factors, the influence of external influence factors on the evaluation results of the established BPNN-based enterprise economic benefit evaluation model cannot be ignored. Figure 4 shows the test results of the enterprise economic benefit evaluation model based on the BPNN.

This study finds that the performance evaluation and prediction of logistics companies are actually affected by many factors. The key is how to find a reasonable and appropriate evaluation method. This paper makes use of the self-organization characteristics of the BPNN and conducts network training research on the weights of evaluation indicators from the statistical data of listed logistics companies. The new method overcomes the shortcomings of the AHP and fuzzy evaluation method, which are influenced by subjective factors, and the results are relatively objective, providing an effective tool for performance evaluation and decision-making of listed logistics companies.

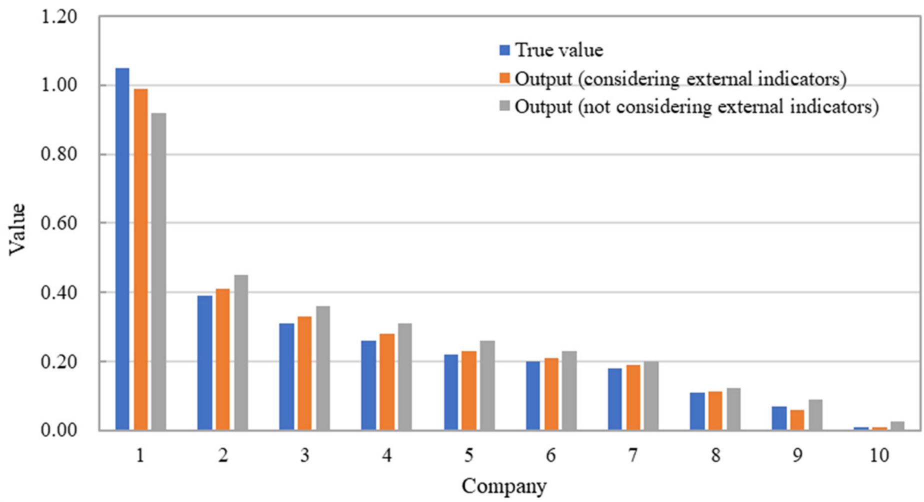
## Model Limitations and Solutions

In-depth analysis of the limitations of the neural network model developed for evaluating the economic benefits of express delivery enterprises in the IoE era reveals several key challenges, along with potential solutions or alternative approaches to mitigate these issues.

### *Sample Size and Representativeness*

**Limitation**. The study relies on data from the top 40 logistics companies, potentially introducing biases and limiting the model's applicability to smaller or less-established enterprises as well as its sensitivity to certain market-specific or operational nuances.

Figure 4. Test results of the enterprise economic benefit evaluation model based on BPNN




**Solutions**. One could include a larger number of companies from diverse tiers within the industry, encompassing not only leading players but also mid-sized and smaller firms, to better capture the full spectrum of economic dynamics and ensure more generalizable results. One could implement a formal sampling framework, such as stratified sampling, to ensure proportional representation of different company sizes, regions, or market segments, thereby reducing selection bias and enhancing the model's ability to account for various market-specific contexts. One could also identify distinct subgroups within the express delivery sector based on shared characteristics (e.g., market positioning, operational strategies, or geographical focus) and develop separate models or adjust existing models to account for these clusters' unique economic behaviors.

### *Data Availability and Quality*

**Limitation**. Dependence on publically available data or voluntary disclosures may lead to incomplete or inconsistent datasets, potentially compromising the model's accuracy and reliability.

**Solutions**. One could establish collaborative relationships with participating companies to secure access to more comprehensive, accurate, and timely data, potentially including proprietary information not available in the public domain. One could employ advanced statistical methods (e.g., multiple imputation or machine learning-based imputation) to fill missing values or correct inconsistencies in the dataset, thereby improving data quality and model robustness. One could also implement rigorous data cleaning procedures and periodic audits to identify and rectify errors, outliers, or inconsistencies, ensuring that the model is trained on reliable and trustworthy data.

### *Model Complexity and Overfitting*

**Limitation**. The BPNN, despite its adaptability, may be prone to overfitting when dealing with limited or noisy data, potentially hindering its generalization capabilities.

**Solutions**. One could incorporate regularization methods, such as L1 or L2 regularization, dropout, or early stopping, to prevent overfitting by imposing penalties on model complexity or terminating training when the validation loss stops improving. One could utilize ensemble techniques, like bagging or boosting, to combine multiple simpler models, thereby reducing the risk of overfitting and improving overall prediction accuracy and stability. One could also leverage pre-trained models or knowledge extracted from similar domains, fine-tuning them for the express delivery context, to alleviate the need for extensive training data and mitigate overfitting risks.

#### *Sensitivity to Operational Strategies*

**Limitation**. The model may not fully capture the impact of unique operational strategies or tactics employed by individual companies, which could significantly influence their economic benefits.

**Solutions**. One could develop domain-specific features that explicitly account for various operational strategies (e.g., route optimization methods, pricing policies, or customer retention initiatives), allowing the model to better understand their contribution to economic performance. One could extend the model to incorporate time-varying components or feedback mechanisms that reflect the effects of strategic adjustments over time, enhancing its ability to capture the dynamic interplay between operational strategies and economic outcomes. One could also supplement the quantitative analysis with qualitative insights from case studies or expert interviews, focusing on how successful companies implement innovative strategies and their subsequent economic impact, to enrich the model's understanding of strategy-driven variations in economic benefits.

#### *Edge Computing Constraints*

**Limitation**. The computational and storage limitations of edge devices may restrict the deployment and performance of complex neural network models, potentially compromising their real-time decision-making capabilities.

**Solutions**. One could employ techniques like pruning, quantization, and knowledge distillation to reduce model size and computational requirements without significantly compromising accuracy, making the model more suitable for resource-constrained edge environments. One could design models that can be partitioned across multiple edge devices or utilize a hierarchical structure, offloading computationally intensive tasks to more powerful cloud servers when necessary, while maintaining low-latency decision-making at the edge. One could also develop algorithms that dynamically adjust model complexity or activation patterns based on the available computational resources and the urgency of the decision-making task, ensuring efficient use of edge resources while maintaining adequate performance.

By addressing these limitations through the proposed solutions and alternative approaches, the neural network model can be refined and adapted to better suit the unique characteristics and challenges faced by express delivery firms in the IoE era, ultimately enhancing its accuracy, generalizability, and practical utility for informed decision-making.

### Comparative Analysis Between Traditional Evaluation Methods and the BPNN-Based Model

In comparing the BPNN-based model with traditional evaluation methods for assessing the economic benefits of express delivery enterprises in the IoE era, it is essential to examine their respective strengths, weaknesses, and implications for model improvement. This comparative analysis aims to provide a comprehensive understanding of the advantages and limitations of each approach, ultimately guiding the development of a more robust and credible model for the express delivery sector.

#### *Traditional Evaluation Methods*

The following are the strengths:

1. Established frameworks: Methods like the balanced scorecard, AHP, and fuzzy evaluation techniques have a well-established theoretical foundation and widespread acceptance across various industries, offering familiarity and ease of adoption.
2. Explicit criteria and weights: These methods often involve explicit definition and weighting of evaluation criteria, fostering transparency and stakeholder understanding of the decision-making process.

3. Quantitative and qualitative integration: Many traditional approaches can accommodate both quantitative data and qualitative assessments, allowing for a holistic evaluation of economic benefits.

The following are the weaknesses:

1. Linear assumptions: Traditional methods often assume linear relationships between variables, which may oversimplify the complex, nonlinear dependencies that govern the economic performance of express delivery firms.
2. Subjective criteria weighting: The assignment of weights to evaluation criteria can be highly subjective, potentially introducing bias and inconsistency in results.
3. Static models: Most traditional methods lack the capacity to adapt dynamically to changing market conditions, technological advancements, or environmental influences, reducing their relevance in the fast-paced IoE context.
4. Limited data utilization: They may not fully exploit the wealth of available data, particularly high-dimensional and temporal data streams, which can offer valuable insights into economic performance.

### *BPNN-Based Model*

The following are the strengths:

1. Nonlinear relationship modeling: The BPNN excels at capturing complex, nonlinear relationships between various internal and external factors affecting enterprise profitability, reflecting the intricate dynamics of the express delivery industry.
2. High-dimensional data handling: It can effectively process large amounts of data, including high-dimensional inputs, allowing for comprehensive consideration of multiple factors influencing economic benefits.
3. Temporal data processing: With the use of RNNs or other time-series modeling techniques, the model can account for temporal patterns in data, crucial for understanding and predicting the effects of changing market conditions.
4. Adaptability and self-learning: Neural networks, through BP, can adapt and update their parameters in response to new data, enabling continuous improvement and real-time decision-making capabilities.

The following are the weaknesses:

1. Transparency and interpretability: Neural networks can be considered “black boxes,” making it difficult to trace the exact reasoning behind predictions or evaluations, which may raise concerns about accountability and trust.
2. Computational complexity and resource requirements: Although edge computing can mitigate some of these challenges, deploying complex neural networks on resource-constrained devices may still pose difficulties in terms of computational efficiency and memory usage.
3. Overfitting risk: Without proper regularization or early stopping mechanisms, neural networks can become overly complex and overfit to the training data, compromising their generalization abilities.

To enhance the quality, credibility, and impact of the BPNN-based model, the following strategies can be implemented:

1. Hybrid models: One could combine the strengths of traditional evaluation methods (e.g., explicit criteria, qualitative integration) with the predictive power of neural networks, creating a hybrid approach that balances transparency, adaptability, and data exploitation.
2. Explainable AI techniques: One could integrate explainable AI methods (e.g., SHAP values, LIME, or attention mechanisms) to enhance the interpretability of neural network predictions, improving stakeholder understanding and trust.
3. Efficient network architectures: One could utilize lightweight or specialized neural network architectures, such as MobileNets or SqueezeNet, designed for edge computing, to reduce computational complexity and memory requirements without significantly sacrificing accuracy.
4. Regularization and early stopping: One could employ regularization techniques (e.g., L1/L2 regularization, dropout) and implement early stopping during training to prevent overfitting and enhance model generalization.
5. Continuous monitoring and model updating: One could establish a framework for continuous monitoring of model performance, periodically retraining or fine-tuning the neural network as new data becomes available or market conditions change.

By conducting a thorough comparative analysis of traditional evaluation methods and the BPNN-based model, identifying their respective strengths and weaknesses, and implementing targeted improvement strategies, the article can significantly contribute to the advancement of enterprise economic benefit evaluation in the express delivery sector, particularly within the IoE context. This comprehensive approach ensures that the model addresses the unique challenges faced by express delivery enterprises while leveraging the latest advancements in data-driven decision-making tools.

## CONCLUSION

The emergence of the IoE era, characterized by innovations such as smart cities and autonomous vehicles, has led to an increased demand for efficient and responsive decision-making in industries like express delivery services. Edge computing, a crucial response to the limitations of centralized computing resources, has become a focal point for enabling real-time data processing and analytics in these contexts. Recognizing the complementary strengths of neural networks and edge computing, this study aimed to develop and validate a BPNN-based economic benefit evaluation model tailored to the specific needs and constraints of express delivery enterprises operating in the IoE landscape.

By focusing on the annual profit rate as the quantitative index of economic benefit and analyzing a carefully selected set of 13 external and internal influencing factors, this research sought to provide a comprehensive and accurate assessment tool for enterprises in the sector. The BPNN model, designed with a single hidden layer structure, was chosen for its proven capacity to handle complex mappings and capture nonlinear relationships between inputs and the economic benefit. The model was trained and validated using financial data from the top 40 logistics companies, with 30 enterprises serving as training samples and 10 for testing, ensuring a balance between model complexity and generalization abilities.

The employed data preprocessing steps, including normalization and appropriate handling of missing values, were critical in preparing the data for efficient neural network training. The choice of resilient BP (Rprop) as the optimization algorithm facilitated effective weight updates and minimized the risk of convergence issues commonly encountered in neural network training. The use of k-fold cross-validation further strengthened the model's reliability by providing an unbiased estimate of its predictive power on unseen data and guarding against overfitting.

Despite the promising results, which demonstrated the model's ability to rapidly and objectively evaluate the economic benefits of express delivery firms and reveal the underlying relationships with influential factors, the study acknowledges inherent limitations and challenges associated with neural networks. Premature convergence of infinitesimal, for instance, must be carefully monitored and addressed during network training and assignment. Moreover, the sample size selection, although guided by practical considerations and a desire for representativeness, warrants further scrutiny in future research. The reliance on the top 40 companies as the sole data source may introduce biases and limit the model's applicability to smaller or less-established enterprises as well as its sensitivity to certain market-specific or operational nuances.

In conclusion, this work contributes to the growing body of research combining neural networks and edge computing technologies to tackle the complexities of enterprise economic benefit evaluation in the ever-evolving IoE environment. The developed BPNN model, while demonstrating good generalization and revealing meaningful insights into the economic dynamics of express delivery firms, underscores the need for ongoing refinement and adaptation of evaluation methodologies to address potential biases, enhance representativeness, and accommodate the unique characteristics and challenges faced by businesses in the IoE era. Future studies should explore ways to expand the sample size, incorporate additional strata of the target population, and employ more rigorous sampling methods to further strengthen the model's generalizability and reduce potential biases. By doing so, the full potential of advanced neural network techniques, seamlessly integrated with edge computing infrastructure, can be harnessed to empower businesses with real-time, data-driven decision-making capabilities that ultimately drive operational efficiency and competitiveness in the express delivery industry.

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