Dynamic Measurement Algorithm for High-Quality Development of Enterprises Using Big Data

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Abstract. This article first reviews the research achievements and current situation of evaluating the high-quality development (HQD) of enterprises, providing theoretical support and a reference basis for algorithm design. Then, based on the research objectives and issues, design and develop a dynamic measurement algorithm suitable for the HQD of enterprises. In the process of algorithm design, this article focuses on data collection and processing, comprehensively considering multiple dimensions such as the financial indicators, market performance, and innovation ability of the enterprise. By constructing a mathematical model and setting key parameters, the various components of the algorithm were successfully implemented and verified through simulation experiments. The results show that the algorithm exhibits good performance in accuracy, stability, and efficiency and can provide timely and accurate assessment results and targeted improvement suggestions for enterprises. This not only helps enterprises understand their own development status in a timely manner and formulate and adjust development strategies but also provides new ideas and methods for research in related fields.

Keywords: Big Data; Computer-Aided Technology; High-Quality Development; Dynamic Measurement Algorithm; Convolutional Neural Network
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1 INTRODUCTION

In the context of globalization, informatization, and Big data provide unprecedented market insight and decision support for enterprises with their massive information capacity, fast data processing ability, and accurate analysis and prediction function. The performance of diagnostic systems directly affects the accuracy and effectiveness of enterprise decision-making. Chebli et al. [1] explored how to use semi-supervised learning techniques to improve the performance of diagnostic systems for high-quality enterprise development and investigated and analyzed them. By utilizing semi-supervised learning techniques, labelled and unlabeled data can be integrated into a unified framework for model training and optimization. This enables it to better adapt to the constantly changing market environment and enterprise development status. The diagnostic results based on semi-supervised learning models can more accurately reflect the high-quality development of enterprises and provide more targeted improvement suggestions for enterprises. Through semi-supervised learning, diagnostic systems can better identify potential problems and opportunities, helping enterprises achieve high-quality development. The influence of online public opinion on enterprises is gradually increasing. Negative public opinion, once spread, may cause irreversible damage to the corporation's image and reputation. Therefore, monitoring and identifying the public opinion of high-risk users is crucial for enterprise risk management and crisis response. Chen et al. [2] explored how to combine user profiling and random forest algorithms to achieve public opinion monitoring and identification of high-risk users. By conducting an emotional analysis of user comments, we can assess their attitudes towards the company, products, or services and promptly identify signs of negative public opinion. By combining user profile data and the evolution law of public opinion, predict possible future public opinion trends and provide a basis for enterprises to formulate response strategies. To verify the effectiveness of high-risk user enterprise public opinion monitoring and identification based on user profiling and random forest algorithm, we can select a company as the case study object. Computer-aided technology greatly improves the production efficiency and management level of enterprises through automation and intelligence.

In today's rapidly developing business environment, small and medium-sized enterprises face many challenges, one of which is how to effectively monitor and manage the operation of their mechanical equipment. Although large enterprises may adopt expensive and complex systems to achieve this goal, such solutions may be too costly for small and medium-sized enterprises. To this end, Chen et al. [3] proposed a low-cost additional sensor and algorithm aimed at helping small and medium-sized enterprises achieve effective mechanical monitoring and scheduling. The core of this solution is an innovative low-cost sensor that can collect and transmit various data about device operation, such as temperature, vibration, current, etc. These data are transmitted wirelessly to the central server and then processed and analyzed through a unique set of algorithms. This algorithm predicts possible faults and issues timely warnings. In addition, the algorithm can also intelligently schedule based on the operational data of devices and the scheduling needs of enterprises. Ding [4] utilizes fuzzy logic and fuzzy reasoning to generate accurate warning signals based on historical data and real-time information and promptly identifies potential risk points. Based on the risk assessment results of fuzzy theory, financial enterprises can develop targeted risk response strategies to reduce risk losses. Intelligent real-time systems can collect various types of financial market data in real-time, process and analyze them quickly, and provide timely and accurate data support for risk warnings. Through intelligent real-time systems, financial enterprises can issue warning signals in a timely manner to remind management and relevant departments to take corresponding measures. A specific financial enterprise was selected as the case study object. Firstly, use fuzzy theory to evaluate and warn of various risks of enterprises. Secondly, by combining intelligent real-time systems, real-time monitoring of risks and rapid release of warning signals can be achieved. Finally, by comparing and analyzing with traditional methods, evaluate the accuracy and efficiency of the system. HQD of enterprises is a core issue in today's economic environment. With the increasingly fierce market competition and the diversification of consumer demand, the development model of simply pursuing scale and speed has been unsustainable. HQD emphasizes innovation-driven, quality and efficiency as the core and realizes sustainable development. This not only requires enterprises to have strong technological innovation ability but also to establish a scientific and systematic development assessment system in order to find problems and adjust strategies in time.

The stability and risk prediction of financial markets have always been a hot research topic. With the advancement of technology, advanced technologies such as deep learning and biomimetic algorithms have provided new perspectives for credit scoring and risk management in financial markets. Du and Shu [5] explored how to use deep learning and biomimetic algorithms to predict and manage credit ratings and risks in financial markets. To verify the effectiveness of deep learning and biomimetic algorithms in financial market credit scoring and risk management, a specific case can be selected for analysis. For example, selecting customer data from a financial institution, constructing a credit rating model using deep learning, and optimizing risk management strategies using biomimetic algorithms. Evaluate the accuracy and advantages of this method by comparing it with traditional credit scoring and risk management methods. By using deep learning to automatically extract features and improve credit scoring accuracy, as well as biomimetic algorithms to optimize risk management strategies and alert market risks, the stability and risk management level of financial markets can be effectively improved. However, in practical applications, issues such as data quality and model generalization ability still need to be considered. The risks in the Internet finance market are becoming increasingly prominent. Therefore, how to effectively manage the risks of the Internet finance market. Data mining and deep learning, as emerging technological means, provide new ideas for solving this problem [6]. For example, selecting P2P lending platforms as research objects, using their historical transaction data and user behaviour data, and using data mining and deep learning methods for risk assessment and prediction, respectively. By comparing and analyzing the results of different methods, we can discover the advantages and disadvantages of data mining and deep learning methods in risk management and further optimize and improve risk management strategies.

Supply chain finance is a financial business that provides financing services for enterprises in the supply chain. In supply chain finance, credit decision-making is a crucial link, and its accuracy directly affects the financing effectiveness of enterprises and the risk management of financial institutions [7]. By extracting complex data features and predicting credit risk through deep learning, combined with fuzzy algorithms to handle uncertainty and fuzziness, enterprise credit risk can be more accurately evaluated, and credit decisions can be made. With the increasing complexity and diversification of financial markets, predicting investor risk behaviour has become an important research field. Investor risk behaviour not only affects individual investment returns but may also have a significant impact on the entire financial market. Therefore, accurate prediction of investor risk behaviour is of great practical significance. Kim et al. [8] explored the application of deep learning in predicting financial risk behaviour and focused on analyzing whether it can accurately predict risky retail investors. Deep learning technology can automatically extract features related to investor risk behaviour from massive data in financial markets, such as trading frequency, trading amount, and position status. These features are crucial for predicting investor risk behaviour. To verify the effectiveness of deep learning in risk prediction for retail investors, we conducted an empirical study. Firstly, we collected a large number of trading records of retail investors from the trading data of a certain securities company. Then, deep learning techniques were used to analyze and model these data, and a predictive model was constructed to evaluate the risk level of retail investors. As a new enterprise development assessment tool, a dynamic measurement algorithm can track the running state of enterprises in real time and accurately reflect the development quality and potential of enterprises. Through the dynamic monitoring and comprehensive analysis of various indicators of enterprises, the dynamic measurement algorithm can help enterprises find potential risks and problems in time and formulate effective countermeasures. Therefore, it is of great significance to study and develop a set of dynamic measurement algorithms suitable for enterprises' HQD so as to enhance their competitiveness and sustainable development ability. This article develops an effective dynamic measurement algorithm to support the assessment and decision-making of enterprises' HQD. The algorithm should be able to collect and process the relevant data of enterprises in real time, accurately reflect the development status and quality level of enterprises, and provide targeted improvement suggestions. Its innovations are as follows:

(1) This article designs a novel dynamic measurement algorithm for HQD of enterprises, which combines various assessment indexes and can comprehensively and accurately reflect the development status and quality level of enterprises.

(2) In the process of algorithm design, this article adopts a unique parameter optimization method and determines the best parameter combination through many experiments and adjustments, which significantly improves the accuracy and stability of the algorithm.

(3) The algorithm designed in this article is highly practical and operable, which can provide enterprises with immediate assessment results and targeted improvement suggestions and help enterprises to know their own development situation in time and make strategic adjustments.

The overall structure of this article is divided into five parts: introduction, literature review and theoretical basis, dynamic measurement algorithm design of HQD of enterprises, simulation experiment and result analysis, and conclusion and prospect. Among them, the introduction mainly expounds on the research background and significance, research objectives and problems, research methods and article structure; the Literature review and theoretical basis part reviews relevant research results and lays a theoretical foundation;

2 LITERATURE REVIEW AND THEORETICAL BASIS

Traditional risk management methods are no longer able to cope with the complexity and uncertainty of the market. Leo et al. [9] explored how to utilize machine learning based on big data and computer-aided technology to enhance the level of bank risk management. By using machine learning algorithms, banks can comprehensively evaluate the credit status of borrowers, including income, expenses, liabilities, credit history, etc. By analyzing historical data, predict the default probability of borrowers and thus decide whether to issue loans and loan amounts. By analyzing historical market data, machine learning models can predict future market trends and help banks formulate reasonable investment strategies and risk control measures. After the model training is completed, it is necessary to evaluate the model and compare its advantages and disadvantages with traditional risk assessment methods. Then, optimize the model based on the evaluation results to improve its performance in practical applications.

Li [10] discussed how to use advanced data analysis techniques and algorithms to evaluate and control the risk financing risks. In the era of big data, data acquisition and analysis have become the key to risk assessment. Firstly, enterprises can utilize big data technology to collect various data related to financing, including financial status, market environment, industry trends, etc. Then, through data mining and machine learning algorithms, these data are analyzed in depth to identify potential risk factors. For example, I used association rule mining algorithms to analyze a company's financial and market data, discover the correlation and regularity between the two, and provide a basis for risk assessment. Risk control is an important means to reduce the probability of risk occurrence and minimize risk losses. In the era of big data, the application of risk control algorithms provides more effective risk control methods for small and medium-sized enterprises. Listed companies are facing unprecedented financial management risks. These risks are influenced by multiple factors and have complex relationships, making risk prediction extremely challenging. Traditional risk prediction methods often struggle to cope with this complexity and uncertainty. In recent years, BP neural networks have achieved significant results in many fields, especially in pattern recognition and prediction [11].

Data mining, as a powerful information processing technology, provides new ideas for solving this problem. Lin [12] discussed how to use data mining methods to construct an innovative risk warning model for application in Internet credit finance risk assessment. Based on historical data and real-time monitoring data, it utilizes data mining techniques to predict potential risks in the future and develop response strategies in advance. By constructing a risk assessment model, the borrower's credit risk is quantitatively evaluated, providing decision support for loan approval and limit adjustment. A specific case was selected for analysis. For example, selecting an internet credit finance institution as the research object, using its historical transaction data and credit information sources to construct an innovative risk warning model. By comparing and analyzing it with traditional risk assessment methods, we can evaluate the performance and advantages of this model and further optimize and improve it. With the widespread application of big data and open-link data in various fields, government enterprises are facing enormous challenges and opportunities. To address these challenges, government enterprises need to develop a cloud computing-based enterprise architecture framework to support the needs of big data and open-link data. Lnenica and Komarkova

[13] discussed how to use cloud computing technology to build such a framework and analyzed its advantages and challenges. Cloud computing can serve as an integrated platform for open-linked data, integrating data from different sources. Through the virtualization technology of cloud computing, government enterprises can easily connect to various data sources to achieve data sharing and exchange. This layer is responsible for collecting data from various data sources, including internal business data, external public data, and other related data. Through distributed collection tools in cloud computing, real-time or batch processing collection of various types of data can be achieved. Integrate open-linked data from different data sources through virtualization technology in cloud computing. Realize data sharing and exchange through unified data interfaces and services.

For public enterprises, this relationship may be more complex as they need to consider more social and environmental goals in addition to pursuing economic benefits. Lucia et al. [14] used machine learning and logistic regression models to explore in depth whether good ESG practices can truly improve the financial performance of public enterprises. Compared to private enterprises, their operational goals are usually more diverse. In addition to economic benefits, they also need to consider public interests, social responsibility, and environmental protection. Therefore, ESG practices are particularly important in these enterprises. Good ESG practices can not only enhance a company's social image but also help it better respond to risks and improve operational efficiency. Overfinancialization, as one of the risks, poses a serious threat to the stable operation and sustainable development of enterprises. Song and Wu [15] discussed how to use data mining and machine learning techniques to evaluate the risk of excessive financialization in financial enterprises and analyze its impact on risk control. Data mining is the process of extracting useful information from a large amount of data, while machine learning is the process of training models to enable machines to automatically learn and summarize patterns from the data. Extract features related to excessive financialization risk from data through machine learning algorithms and construct predictive models. These models can be used to identify potential risk points of excessive financialization. Based on the constructed model, evaluate the risk of excessive financialization in financial enterprises and issue warnings based on the evaluation results to help enterprises take timely response measures. By mining and analyzing its historical data, a risk assessment model is constructed using machine learning algorithms, and the risk of excessive financialization is evaluated.

Investors make claims to companies through online platforms, reflecting their concern for the company's business behaviour and capital structure. Yue et al. [16] explored the impact of online investor claims on corporate capital structure and provided evidence for the study using big data and computer-aided technology. Online claims by investors may have multiple impacts on a company's capital structure. On the one hand, a large number of investor claims may lead to financial pressure on companies, thereby affecting their capital structure. On the other hand, online claims by investors may cause fluctuations in a company's stock price, further affecting the company's financing decisions and capital structure. In addition, online investor claims may also encourage companies to pay more attention to information disclosure and investor relationship management in order to reduce capital costs and optimize capital structure. By collecting and analyzing a large amount of investor online claim data, one can gain a deeper understanding of investor behaviour, corporate financial conditions, and market reactions. Meanwhile, utilizing computer-aided technology for data mining and model construction can help us more accurately identify the factors that affect a company's capital structure and provide a basis for formulating reasonable financing strategies.

With the development of technology and the intensification of global competition, enterprises are facing increasingly diverse risks, especially financial risks. How to effectively warn and respond to financial risks has become an important issue for the sustainable development of enterprises. The application of advanced technologies such as the Internet of Things and rough set theory provides new ideas for solving this problem [17]. Build a BP neural network model based on the processed data. You can choose a neural network structure with three or more layers and adjust it according to actual needs. When constructing a model, it is necessary to optimize the parameters of the neural network, such as learning rate, number of iterations, number of hidden layer neurons, etc., in order to improve the prediction accuracy and generalization ability of the model. Train the model using known financial risk data and validate and optimize the model using a validation set. Cross-validation, grid search, and other methods can be used to tune and optimize the model to improve its prediction accuracy and stability. Apply the trained model to actual financial risk warnings, determine whether the enterprise has financial risks based on the output results of the model, and provide corresponding warning prompts. At the same time, further analysis and processing of warning results can be conducted, providing more in-depth risk analysis and response strategies. In order to address this challenge, enterprises need to continuously improve their own level of high-quality development. However, dynamically measuring the high-quality development of enterprises is a challenging issue [18]. Computer-aided technology is used to extract features related to high-quality development from preprocessed data. Taking a manufacturing enterprise as an example, this article provides a detailed introduction to the application process of a dynamic measurement algorithm for the high-quality development of enterprises based on big data and computer-aided technology. Firstly, collect financial data, market data, and technical data of the company in recent years. Then, feature extraction techniques are used to extract features related to the high-quality development of the enterprise from the data. Next, we will use the support vector machine algorithm to construct a high-quality development measurement model and optimize the model through cross-validation.

3 DESIGN OF DYNAMIC MEASUREMENT ALGORITHM FOR HQD OF ENTERPRISES

3.1 Principles and Requirements of Algorithm Design

In academic circles, the assessment of enterprises' HQD has become a research hotspot. Many scholars and experts have conducted in-depth research and discussion on the HQD of enterprises from different angles and using different methods. These studies mainly focus on the construction of an assessment index system, the innovation and application of assessment methods, and the empirical analysis of assessment results. However, despite the fruitful research results, there are still some problems and shortcomings. First of all, the selection of assessment indicators and the distribution of weights are subjective and arbitrary, lacking unified standards and norms. Secondly, the existing assessment methods mostly focus on static analysis, which makes it difficult to reflect the dynamic development process and future trends of enterprises. Finally, due to the limitation of data acquisition and processing, the accuracy and reliability of the assessment results need to be further improved.

As big data and computer-assisted technologies continue to advance rapidly, a growing number of scholars have ventured into applying these innovations to the field of enterprise assessment. Furthermore, the integration of computer-aided technologies, including artificial intelligence and machine learning, has become prevalent in developing and refining assessment models. This integration not only elevates the precision and speed of evaluations but also transforms the assessment process into a more sophisticated and intelligent endeavour. In addition, these technologies can also help enterprises realize real-time monitoring and early warning, discover potential risks and problems in time, and provide strong support for enterprise decision-making.

Dynamic measurement algorithm is an analysis method based on time series data, which reflects the development state and quality level of enterprises through dynamic monitoring and comprehensive analysis of various indicators of enterprises. Its basic principle is to use mathematical models and calculation methods to transform the indexes of enterprises into comparable numerical forms and to reveal the internal relations and changing laws among indexes through time series analysis and other methods. In the design of a dynamic measurement algorithm, the key factors that should be considered include the selection and processing of indicators, the distribution and adjustment of weights, and the selection and optimization of calculation methods. First of all, it is necessary to select indicators that can fully reflect the development of enterprises and carry out appropriate treatment to eliminate the influence of dimensions and orders of magnitude. Secondly, it is necessary to allocate corresponding weights according to the importance and relevance of each index and adjust them according to the actual situation. Finally, it is necessary to choose an appropriate calculation method to comprehensively process and analyze the indicators and get the final assessment results.

Possible technical routes include methods based on statistical analysis, methods based on machine learning and hybrid methods. The method based on statistical analysis mainly uses regression analysis, principal component analysis and other means to process and comprehensively analyze the indicators. The method based on machine learning predicts and evaluates the development state of enterprises by constructing classifiers and regression models. The hybrid method combines the advantages of two or more methods to design and optimize the algorithm. When designing the dynamic measurement algorithm for enterprises' HQD, this article follows the guiding principles in Table 1 to ensure the effectiveness and practicability of the algorithm. The functional requirements and performance requirements are shown in Table 2:

Guiding principle	*Analysis*
Accuracy	The algorithm must be able to accurately reflect the development status and quality level of the enterprise and avoid misleading assessment results.
Real-time	The algorithm should have real-time processing ability so as to track the running state of the enterprise in time and provide real-time assessment results.
Expandability	The algorithm should be easy to expand and update to adapt to the ever-changing enterprise development environment and assessment needs.

Table 1: Guiding principles.

Functional requirements	*Analysis*	*Performance requirement*	*Analysis*
Data collection and processing	The algorithm should be able to collect and process the relevant data of enterprises, including financial indicators, market performance, innovation ability and other dimensions.	Efficient data processing	The algorithm should have efficient data processing ability to ensure that accurate assessment results can still be generated quickly in the big data environment.
Comprehensive assessment and improvement suggestions	Provide comprehensive assessment results and targeted improvement suggestions.	Stable operation performance	The algorithm should have stable running performance.
Multiuser support	Support multiuser simultaneous access and operation.	Fault tolerance and exception handling	The algorithm should have certain fault tolerance and exception handling ability to avoid assessment interruption or result distortion caused by data abnormality or system failure.

Table 2: Functional requirements and performance requirements.

3.2 Data Collection and Processing

In order to support the operation of a dynamic measurement algorithm, it is necessary to collect and process internal data and external market data. Internal data of enterprises include financial statements, sales performance, R&D investment, human resources and other information, which mainly reflect the internal operation and development potential of enterprises. External market data includes industry trends, competitors, policies and regulations, and other information, which is helpful in understanding enterprises' external environment and market competition situation.

In the process of data collection, data will be obtained through various channels, including internal databases and enterprise information systems, public market research reports and statistical data, and public information from government departments. Moreover, in order to ensure the integrity of the data, this article carries out preprocessing operations such as cleaning, removing duplicates and filling in missing values. Appropriate data standardization methods are adopted to eliminate the dimensional and order differences between different indicators and improve the comparability of data.

3.3 Concrete Design and Implementation of Algorithm

The dynamic measurement algorithm of an enterprise's HQD mainly includes the following components:

Mathematical model: Select the mathematical model suitable for the HQD assessment of enterprises as the basis, and this article adopts the convolutional neural network (CNN) model. In the assessment of enterprises' HQD, there are many interrelated factors, such as financial indicators, market performance, innovation ability, social responsibility, and so on. These factors affect the development of enterprises in different ways, and there is a complex nonlinear relationship between them. Traditional linear models or statistical methods are often difficult to accurately capture these relationships, while the CNN model can automatically construct complex mapping relationships between factors by learning the inherent laws and characteristics of data. Convolution stands out as the pivotal component within CNN, tasked with extracting crucial feature information from data. The mathematical representation of discrete convolution takes the form as follows:

$$H\ x,y\ = A \otimes k\ x,y\ = \sum_{M,N} A\ m,n\ k\ x-m,y-n \tag{1}$$

Assume that the l layer is a fully connected layer, the weight matrix is W^l, and the offset is b^l. The calculation process of the fully connected layer is shown in Formula (2), and the input of the fully connected layer is shown in Figure 1.

$$Z_j^l = f\ W^l X^{l-1} + b^l \tag{2}$$

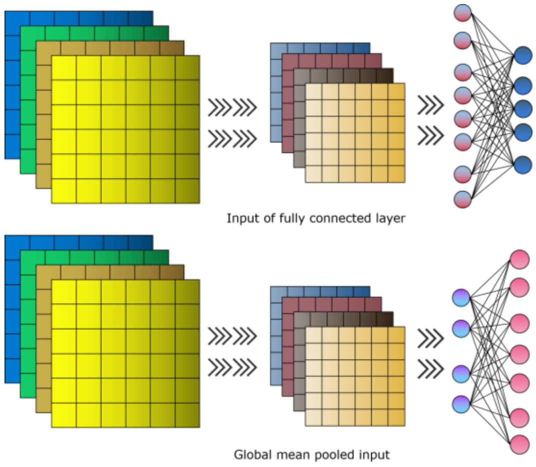

Figure 1: Input of full connection Layer.

Due to the limited expressive capabilities of linear models, nonlinear activation functions are incorporated into neural networks to generate a nonlinear response to inputs, thereby achieving nonlinear modelling. Presently, the ReLU function is commonly employed as the activation function in this context:

$$f\ \ x\ \ = \max\ \ 0, x \tag{3}$$

Its computational speed is notably quicker, leading to expedited network training. CNN recognizes the invocation of function sim :

$$y = sim\ \ net, P \tag{4}$$

In this context, net it represents the designated name of the trained neural network while P denoting either the input vector for training samples or the input vector for test samples. y Stands for the computed output vector that corresponds to P . Given the input vector X_n , the N_{new} k -th component of the output layer is denoted as y_k :

$$y_k = \sum_{j=1}^{Q} w_{jk} * f_j \tag{5}$$

$$f_j = F\ \ X_j, X_n \tag{6}$$

Among them, $F\ \cdot$ it represents the basis function, and different functions can be selected according to the situation, X_j it represents the centre of the j -th basis function and X_n is the input vector.

The CNN model used in this article has a multi-layer network structure, which can extract the features of input data layer by layer and abstract and integrate them at higher levels. Through a large amount of training data, the model can learn the weights and patterns of various factors affecting the HQD of enterprises, thereby achieving an accurate assessment of their development status.

Calculation process: The calculation process of the algorithm includes steps such as data input, preprocessing, model training, and output of assessment results. At each step, appropriate methods and techniques are adopted to ensure the accuracy and efficiency of calculations. During the model training phase, methods such as cross-validation are used to optimize model parameters and improve the model's generalization ability. This article introduces an inertia weight factor w in the model to balance the global search and local search capabilities. w It is used as the inertia weight and w is determined by the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} \times t \tag{7}$$

Among them $w_{\max}, w_{\min}$ are the maximum and minimum values w , respectively. Moreover, normalize the original data and limit the input data to between [-1,1]. The formula is as follows:

$$data_{norm} = 2 * \left(\frac{data - data_{\min}}{data_{\max} - data_{\min}} \right) \tag{8}$$

Among them $data_{\min}$ are the smallest pressure value in all training data sets, $data_{\max}$ the largest pressure value in all training data, $data$ the current sample data, and $data_{norm}$ the normalized data.

Parameter configuration plays a pivotal role in determining the precision and consistency of assessment outcomes. In this study, parameter values are carefully chosen based on specific circumstances and prior knowledge, with their efficacy confirmed through rigorous experiments. Additionally, to accommodate individual requirements, a feature allowing users to customize parameters will be made available.

During implementation, several notable technical challenges arise, including data imbalance and model overfitting. To address these issues, the following strategies are employed: (1) To mitigate data imbalance, techniques such as over-sampling or under-sampling are utilized to equilibrate diverse datasets, thereby enhancing the model's classification proficiency. (2) To tackle model overfitting, a multifaceted approach is adopted, encompassing regularization, expanding the sample size, and pruning redundant features. These measures serve to streamline the model's complexity and bolster its ability to generalize. (3) Furthermore, the integration of a validation set into the model training workflow emerges as a potent tool for real-time monitoring, effectively curbing the risk of overfitting.

4 SIMULATION EXPERIMENT AND RESULT ANALYSIS

4.1 Experimental Environment and Data Preparation

To validate the dynamic measurement algorithm's efficacy and applicability for HQD assessments of enterprises, this segment undertakes simulation experiments. The experimental setup necessitates a hardware and software infrastructure comprising high-performance computers, along with pertinent programming languages and data manipulation utilities. For data resources, authentic enterprise datasets spanning multiple industries are utilized, encompassing a wide range of dimensions, including financial metrics, market achievements, and corporate innovation prowess.

During the preparatory phase of experimental data, the datasets undergo rigorous sampling techniques to ensure a representative and diverse sample pool. Additionally, to eradicate disparities in dimensions and sequencing across various indicators, the data undergoes standardization, aligning all indicators to a uniform scale. This standardization facilitates subsequent computations and analytical procedures.

4.2 Experimental Process and Parameter Setting

During the experimental process, the operations are systematically executed in accordance with the algorithmic calculation flow. Initially, the preprocessed data is fed into the algorithm. Subsequently, the training dataset is utilized to refine and enhance the algorithm's performance. Ultimately, the algorithm's proficiency is gauged using the test dataset, and the evaluation outcomes are disseminated. Within the experimental framework, the calibration of pivotal parameters plays a crucial role in shaping the algorithm's performance. In this segment, the initial parameters are judiciously chosen based on specific circumstances and prior expertise. The optimal parameter configuration is ascertained through iterative experimentation and fine-tuning. Furthermore, to ascertain the algorithm's stability and dependability, multiple experiments are conducted with varying parameter configurations. The outcomes are then subjected to comparative analysis. The experimental findings pertaining to learning rate adjustments are graphically represented in Figure 2.

When the learning rate is too high, the algorithm oscillates in the training process, and it cannot converge stably, which leads to the decline of model performance. Therefore, when choosing the learning rate, we need to weigh the convergence speed and stability. According to the experimental results in Figure 2, a moderate learning rate range can be determined, which can not only ensure the fast convergence of the algorithm but also avoid the occurrence of oscillation. In this experiment, the best learning rate is determined to be 0.006, which makes the algorithm converge stably and achieve better performance. The results of the regularization parameter setting are shown in Figure 3.

Regularization parameters serve as safeguards against over-fitting and enhance a model's capacity for generalization. Our findings indicate that as these parameters increase, training set errors rise steadily. Meanwhile, test set errors initially decline but later rise again. This underscores that appropriately set regularization parameters can regulate model complexity and mitigate over-fitting risks. Nevertheless, excessively high regularization parameters can overly simplify the model, preventing it from capturing key data features. This, in turn, diminishes test set performance. Consequently, selecting regularization parameters requires striking a careful balance: ensuring the model grasps data nuances while preserving strong generalization capabilities. In our study, the ideal regularization parameter was pinpointed at 0.01. The results of the batch size setting are shown in Figure 4.

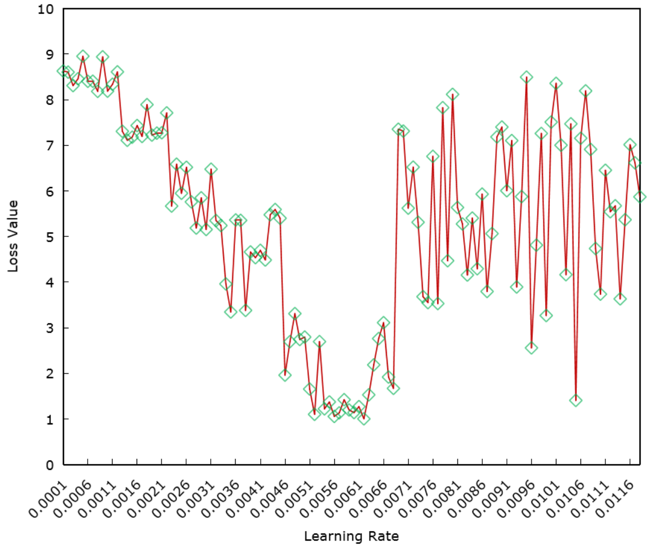

Figure 2: Learning rate.

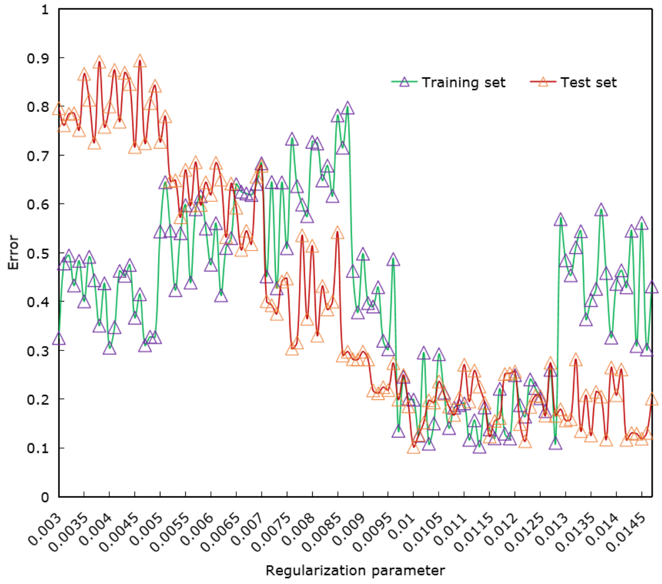

Figure 3: Regularization parameters.

The batch size determines the number of data samples used to update the model weights in each iteration. The experimental results show that when the batch size is small, the algorithm can converge to the optimal solution faster, but the stability of the algorithm is poor due to the small number of data samples updated in each iteration, which is easily affected by noise data.

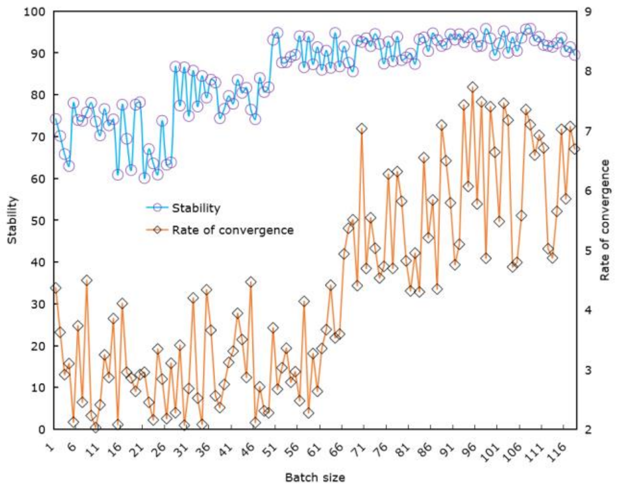

Figure 4: Batch size.

With the increase in batch size, the stability of the algorithm is gradually improved, but the convergence speed is slow. Therefore, when choosing the batch size, it is necessary to balance the convergence speed and stability. In this experiment, it is found that when the batch size is 64, the algorithm achieves a good balance between convergence speed and stability. This value not only ensures the fast convergence of the algorithm but also gives the algorithm good stability in the training process.

In addition to adjusting its own algorithm parameters, this section also compares this method with other similar algorithm models (RNN, BPNN) to highlight the innovation and superiority of this algorithm. The accuracy of different algorithms is shown in Figure 5.

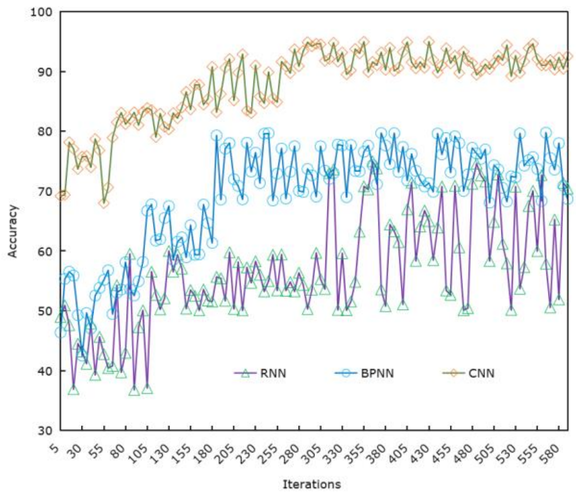

Figure 5: Accuracy of different algorithms.

Figure 5 clearly shows that the accuracy of this algorithm is better than the other two algorithms on the test data set. This shows that this algorithm can capture the characteristics of data more accurately when dealing with the assessment of enterprises' HQD so as to make more accurate predictions and judgments. The stability of different algorithms is shown in Figure 6.

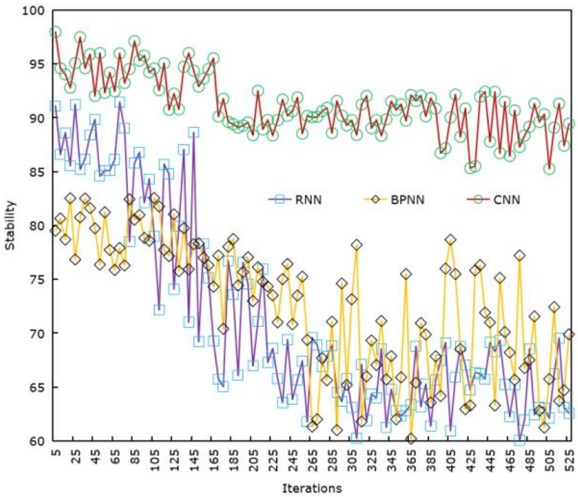

Figure 6: Stability of different algorithms.

In terms of stability, this algorithm also shows significant advantages. As shown in Figure 6, the performance fluctuation of this algorithm is small under the data set, while the RNN and BPNN algorithms show great instability. This shows that this algorithm is more robust in dealing with data changes and environmental disturbances and can provide high-quality assessment results more consistently. This stability enhancement is very important for the reliability requirements in practical application scenarios. The efficiency of different algorithm models is shown in Figure 7.

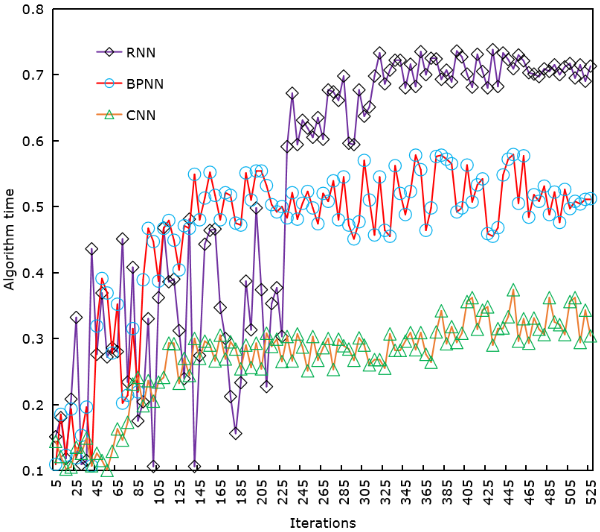

Figure 7: Efficiency of different algorithm models.

In terms of efficiency, the efficiency of this algorithm is slightly higher than that of RNN and BPNN. Moreover, considering its remarkable advantages in accuracy and stability, it shows that the model in this article is reliable. The applicability of this model in different industries and enterprises of different scales is shown in Figure 8 and Figure 9.

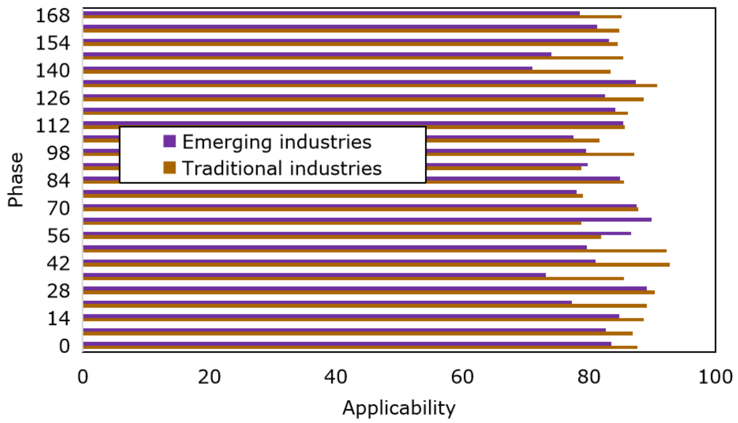

Figure 8: Applicability of the model in enterprises of different industries.

As can be seen from the figure, the model in this article shows high accuracy in both traditional industries and emerging industries. This shows that this model has strong cross-industry applicability and can capture the common characteristics and laws of different industries.

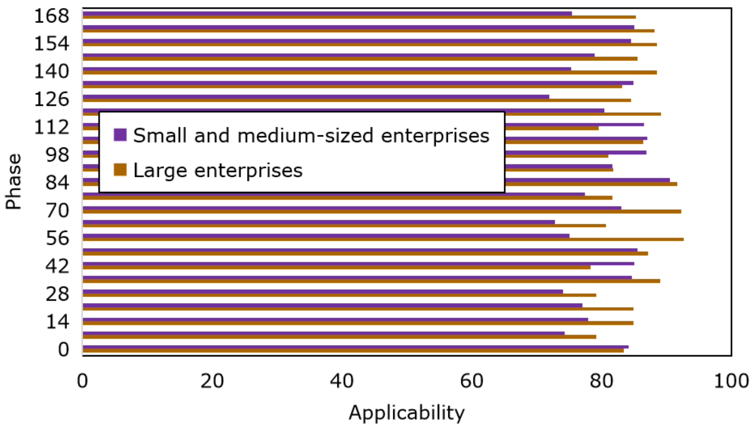

Figure 9: Applicability of the model in enterprises of different scales.

Whether it is a large enterprise or a small or medium-sized enterprise, this model has maintained a relatively stable performance. This shows that this model has good scale adaptability and can meet the assessment needs of enterprises of different scales.

Through the analysis of Figure 8 and Figure 9, we can draw the following conclusions: This model has good applicability and generalization ability in different industries and enterprises of different scales. This provides a powerful assessment tool for enterprises to achieve HQD and helps to promote the sustainable growth of enterprises in different industries and scales.

4.3 Experimental Results and Discussion

Through experiments, the main results of the dynamic measurement algorithm for HQD of enterprises in accuracy, stability and efficiency are obtained. The algorithm shows a high performance level in all indicators, which can accurately reflect the development status and quality level of enterprises. Moreover, the algorithm runs faster and can meet the needs of real-time assessment. After in-depth analysis and discussion of the results, this article finds that the algorithm has good applicability and generalization ability in different industries and enterprises of different scales. This shows that the design and implementation of the algorithm are successful and can provide strong support for the HQD assessment of enterprises.

Through the simulation experiment and result analysis, this article verifies the effectiveness and practicability of the dynamic measurement algorithm for enterprises' HQD. The algorithm can provide accurate and real-time assessment results and targeted improvement suggestions for enterprises, which is helpful in promoting enterprises to achieve HQD.

5 CONCLUSIONS AND SUGGESTIONS

5.1 Research Conclusion

Focusing on the core problem of enterprise HQD assessment, this study designs a dynamic measurement algorithm, verifies it by simulation experiments, and draws the following main conclusions:

Dynamic measurement algorithms have shown remarkable advantages in evaluating enterprises' HQD. The algorithm can comprehensively consider multi-dimensional data information, track the development state of enterprises in real time, and provide accurate and objective assessment results. This is of great significance for enterprises to know their own development situation in time and formulate and adjust their development strategies. Moreover, the dynamic measurement algorithm designed in this study shows good performance in accuracy, stability and efficiency. The results show that the algorithm has good applicability and generalization ability in different industries and enterprises of different scales and provides a new and effective tool for the assessment of enterprises' HQD. This study not only provides theoretical support and technical means for the assessment of enterprises' HQD but also provides new ideas and methods for research in related fields. The design concept and implementation method of dynamic measurement algorithm have certain reference significance for the research of other similar problems.

Although this study has achieved remarkable results in theory, some potential problems and challenges still need to be considered in practical application. First of all, when applying dynamic measurement algorithms, enterprises need to collect and process data according to their own actual situation to ensure the integrity of data. Secondly, due to the differences in the development characteristics of different industries and enterprises, it may be necessary to adjust and optimize the model parameters when using the algorithm to improve the accuracy and pertinence of the assessment.

5.2 Practical Application and Suggestions

In order to promote the application and popularization of dynamic measurement algorithms, this article puts forward the following specific suggestions:

(1) Strengthen the capacity building of enterprise data management. Enterprises should establish a perfect system of data collection, processing and analysis, improve the quality and availability of data, and provide strong data support for the application of algorithms.

(2) Promoting cooperation and exchanges in Industry-University-Research. By building a cooperation platform in Industry-University-Research, the communication and cooperation between academia and industry will be strengthened, and the continuous improvement and perfection of dynamic measurement algorithms in practical application will be promoted.

(3) Carry out training and promotion activities. Carry out relevant training and promotion activities for enterprise managers and technicians to improve their understanding and application ability of dynamic measurement algorithms and promote their wide application in enterprises.

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