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The Synergistic Pathway of High-Performance Computing Empowering New Productivity and Economic Policy Innovation within a Political Economy Framework

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Abstract The application of high-performance computing technology in product quality testing can improve enterprise productivity and product quality, creating conditions for the development of new quality productivity, which needs to be supported and guided by economic policy innovation. This study explores the potential of high-performance computing technology, especially the application of random forest model in product quality inspection for the improvement of new quality productivity and economic policy innovation. By constructing a product quality inspection system based on the random forest model and applying it to enterprise production practice, the impact of high-performance computing on enterprise productivity and economic efficiency is analyzed. The study uses a combination of experimental validation and enterprise case study to comparatively analyze the changes in the economic indicators of enterprises before and after the application of the technology. The results show that the product quality inspection system based on the random forest model shortens the average beat time of the enterprise by 28.56%, and the fault prediction accuracy rate reaches 98.54%; after the implementation of high-performance computing technology in enterprise A, the return on net assets in 2024 is 16.97% higher than the industry average, and the inventory turnover rate increases to 10.13 times. Based on the empirical analysis, this paper proposes three economic policy innovation paths, namely, optimizing the design of tax incentives, adjusting the structure of fiscal science and technology investment and enhancing the synergy of industrial support policies, in order to support the application of high-performance computing technology in a wider range of fields and promote the development of new-quality productive forces, which provides a theoretical basis for the formulation of relevant economic policies.

Index Terms Random forest model, product quality inspection, high performance computing, new quality productivity, economic policy innovation, enterprise economic efficiency

I. Introduction

In recent years, China's economy has boomed and become the largest economy in the world, and economic policy is an important foundation for this development. The Chinese government has formulated a series of economic policies to promote the development of the economy, which are all centered on China's medium- and long-term economic development goals [1], [2]. In the traditional economic policies, with the transformation of economic structure and economic development, the GDP accounting system exposes defects in the extraction of hidden value and the definition of intellectual property rights, and the regulatory system of financial derivatives is backward [3]-[5]. The governance mechanism of international economic market lags behind, the imbalance of arithmetic pricing strategy related to engineering projects, and the imbalance of arithmetic supplier distribution, close to 80% of enterprises with low supercomputing resources, as well as the arithmetic carbon footprint constrains the green subsidy policy [6]-[9]. In recent years, with the changes in the global economic situation and the needs of China's economic development, economic policies need to be constantly adjusted and optimized.

The enhancement of new quality productivity is related to the high-quality development of the economy and the realization of socialist modernization, supplying a new direction for the formulation of economic policies [10], [11]. The breeding of new quality productivity originates from technological breakthroughs, innovative allocation of production factors and deep transformation and upgrading of industries, and is based on the optimal combination of laborers, labor materials and labor objects, reflecting innovative, efficient, high-quality and strategic characteristics [12], [13]. This new quality productivity is different from traditional productivity, driven by innovation, representing a qualitative leap in productivity and the core of scientific and technological innovation. New quality productivity can enhance total factor productivity, etc., and the input of arithmetic power further enhances total factor productivity, but it may also bring the risk of employment and income inequality [14]. Therefore, it is important to continuously improve the new quality productivity.

With the continuous development of science and technology, high-performance computing is being widely used in various fields. It utilizes powerful computer processing capabilities to simulate, analyze, and solve complex scientific, engineering, and business problems. Using high-performance computing, financial institutions and economic research institutes can perform large-scale data analysis and computation, simulate and predict changes in the economic market, and provide scientific financial decision support [15], [16].

Contemporary economic development has entered the stage of high-quality development, the productivity pattern is undergoing profound changes, and high-performance computing technology, as an important tool in the era of digital economy, is changing the traditional production methods and economic structure. In the field of industrial production, product quality inspection is a key link to ensure the performance and safety of products, and traditional inspection methods have problems such as low efficiency, insufficient accuracy and high cost. The application of high performance computing technology, especially machine learning algorithms, provides new ideas for product quality inspection. Among them, the random forest model has become a powerful tool for product quality inspection due to its excellent classification and regression capabilities, as well as its advantages in processing high-dimensional data. However, there is a lack of research on how HPC technology can promote the new quality productivity of enterprises through product quality inspection, and how the corresponding economic policies can be innovated to adapt to this change. The application of high-performance computing technology involves enterprise decision-making, industrial transformation and economic restructuring, and the relevant government economic policies need to be adapted to the development of the technology in order to play a greater role. Currently, fiscal policy, industrial policy and science and technology policy have not yet formed a synergy in supporting the application of high-performance computing technology, and there is a mismatch between the policy supply and the demand for technology application. Therefore, it is of great theoretical and practical significance to study the potential of high-performance computing to promote new quality productivity enhancement for economic policy innovation from the perspective of political economy. The wide application of high-performance computing technology will reshape the industrial chain and value chain and bring about the adjustment of production relations, which needs to be guided and regulated by economic policies to realize the benign interaction between technological progress and economic and social development.

In this study, the impact of the application of high-performance computing technology on the production efficiency and economic benefits of enterprises is deeply analyzed by constructing a product quality inspection system based on the random forest model. Firstly, the basic principles of random forest model and its application in product quality detection are theoretically elaborated; secondly, the product quality detection system based on random forest model is designed and implemented, and its effect in product quality detection is experimentally verified; then, the impact of high-performance computing technology on the profitability, operating ability and development ability of Enterprise A is analyzed through case studies; finally, based on the empirical research results, an economic policy innovation path adapted to the development needs of the new quality productivity is proposed. This study adopts the methods of combining theoretical analysis and empirical research, qualitative analysis and quantitative analysis, and reveals the economic effects of the application of high-performance computing technology by comparing horizontally and analyzing vertically the changes in the enterprise's economic indexes, which provides a scientific basis for policy formulation.

II. The role and application of random forests in high performance computing of enterprise data

II. A. Random Forest Model

Random Forest is an integrated learning based algorithm that improves model performance by constructing multiple decision trees and combining their predictions. The method adopts the idea of Bootstrap Aggregating [17] with putback to model the training samples with decision trees and make decisions by combining multiple decision trees to produce the final results, so it is also known as Random Decision Tree. Randomized decision tree structure is shown in Figure 1, the basic process of random forest decision making is mainly divided into three steps:

(1) Generating training subsets of decision trees

To build N decision trees, N training subsets need to be prepared, and this process is achieved by applying statistical sampling methods from the original training set to ensure that each decision tree has a corresponding training dataset.Bootstrap Aggregating, referred to as the self-help method. Based on Boosting technique. It uses repeatable random sampling, i.e., putative back sampling from the initial dataset to generate multiple training subsets. In this process, all the samples in the initial training set may be sampled, but after multiple sampling, there may still be samples that are not sampled with a probability of $\left(1-\frac{1}{N}\right)^{N}$, where N is the number of samples in the original training set. This probability tends to e^{-1} as the number of samples tends to infinity. Therefore, the training subset maintains the same volume as the original training set, and for the remaining unselected samples in the original training set, they can be used as the validation dataset of the model.

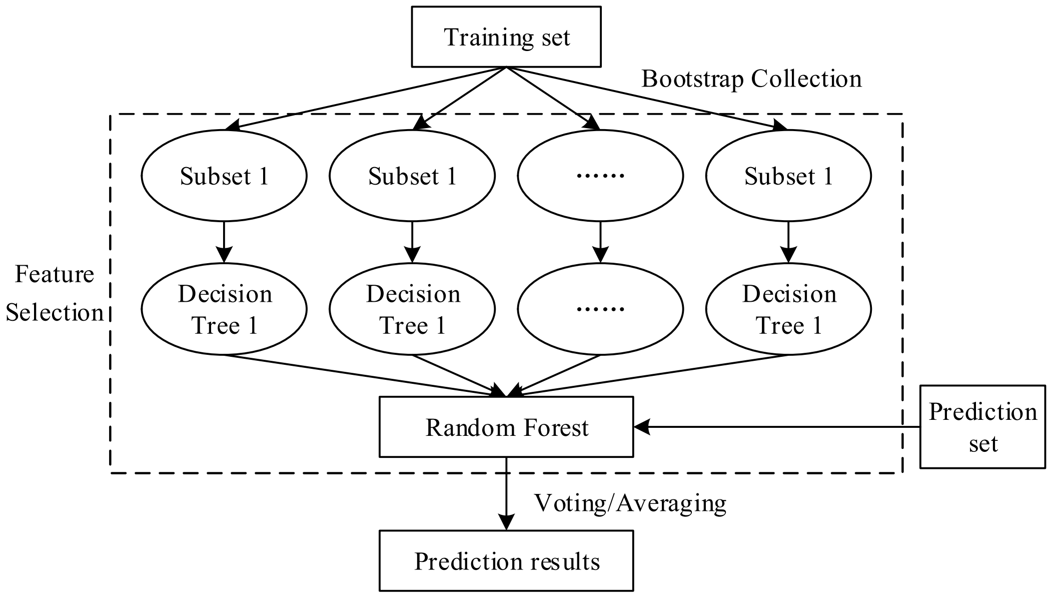

Figure 1: Stochastic forest decision process

(2) Constructing Decision Trees

Each training subset is utilized by constructing a decision tree, which ultimately creates an ensemble of N decision trees, the so-called "forest". In this process, each tree is allowed to grow naturally to its maximum without pruning. Two key processes are node splitting and random selection of feature variables.

Node splitting is a key step in the construction of a decision tree and is designed to facilitate the growth of the tree by selecting different attributes. This process follows rules such as maximizing the information gain, information gain rate, or minimizing the Gini coefficient, each of which corresponds to a specific splitting algorithm.The CART algorithm determines the splitting nodes based on the Gini coefficient, whereas comparatively the C4.5 algorithm employs the information gain rate as the basis for its splitting.The CART algorithm is favored because of its robustness and is suitable for processing both continuous and discrete data, especially for small sample datasets containing missing values, it is effective in preventing overfitting phenomena.

The Gini index [18] is defined as follows: assuming that there is a sample set Y to be tested, which contains N classes of experimental samples, the Gini index $Gini(Y)$ is computed as follows:

$$Gini(Y)=\sum_{k=1}^{N} p_k(1-p_k)=1-\sum_{k=1}^{N} p_k^2 \tag{1}$$

Here p_k denotes the probability of belonging to the k th class of samples in Y. If Y is divided into two subsets $Y1$ and $Y2$, the Gini indices of these two parts are respectively:

$$Gini(X_1,X_2)=\frac{X_1}{|X|}Gini(X_1)+\frac{X_2}{|X|}Gini(X_2) \tag{2}$$

The best node splitting method can be identified by calculating and comparing the Gini index under different splitting schemes.

In random forest algorithms, Forest-RI and Forest-RC are the two main random feature variable generation strategies. These two strategies enhance the diversity of the model by introducing randomness in feature selection, which helps to improve the generalization performance of the model to unknown data.

Forest-RI method: this method constructs a decision tree based on a fixed number of F attributes by randomly selecting a fixed number of attributes from the full set of available attributes at each node split, and then constructing a decision tree based on these randomly selected attributes. Here, the selection of F is usually based on experimental or empirical rules, and there are two typical choices: one is to simply set $F=1$, and the other is to let F be equal to the largest integer that is less than or equal to $\log_2 M+1$, where M is the total number of input variables.The Forest-RI method enhances the robustness of the model by this random attribute selection mechanism, although in the case of a small number of attributes number is small, it may slightly increase the correlation between trees, but overall it can effectively improve the accuracy of the model.

Forest-RC method: compared to Forest-RI, the Forest-RC method further adds stochasticity by not only randomly selecting input variables, but also by randomly combining these variables to create new features for the tree generation process. This method can create more diverse decision trees to some extent, increasing the uniqueness and generalization ability of the model.

In practice, Forest-RI is the more commonly used random forest construction strategy. This method makes the generation of each tree not completely dependent on all the input variables M, but on a small number of randomly selected F feature variables $(F \le M)$. In this way, not only does it increase the diversity of decision trees in the model, but it also introduces randomness in finding the optimal splitting point, effectively improving the overall performance of the model. This combination of stochastic feature selection and multiple decision trees allows random forests to exhibit superior model accuracy and robustness when dealing with a variety of datasets.

(3) Generating Random Forests

Performing the process of building trees N times will produce N decision trees corresponding to their particular training dataset, which together form the structure of the random forest. In the prediction phase, new input samples will enter these trees separately, and each tree makes predictions independently. When dealing with classification problems, the random forest pools the predictions of all the individual trees and decides the class to which the sample belongs through a voting mechanism. For regression tasks, the average of the predictions of all decision trees is used as the final prediction.

Through the above steps, Random Forest can effectively synthesize the knowledge of multiple decision trees, reduce the risk of overfitting, and improve the accuracy and stability of prediction. Of course, Random Forest has some limitations. First, the interpretability of the model is relatively poor, and it is difficult for us to understand the meaning of each branch and node of the decision tree. Second, in the case of high-dimensional data and large samples, the training and prediction time of random forest will be longer. In addition, Random Forest may be less suitable for some data with strong linear relationships, because it is better at dealing with non-linear feature relationships.

Overall, Random Forest, as a powerful machine learning algorithm, shows a wide range of application potential. It can not only effectively handle large amounts of data and complex feature relationships, but also provide accurate prediction results and importance assessment of features. However, when using Random Forest, it is necessary to have a deep understanding of its algorithmic principles and appropriate application occasions in order to more effectively utilize this technique to solve real-world problems.

II. B. Random Forest Modeling in Product Quality Testing

Random forest modeling obtains final product quality inspection results by constructing multiple decision trees and voting or averaging them. In product quality inspection, facing diverse data sources (e.g., production environment parameters, chemical composition, microbial indicators, etc.), the random forest model, with its randomness and high efficiency, is able to extract key features from complex and high-dimensional data and provide powerful support for quality assessment and classification. Therefore, this paper investigates the design and validation of a big data analysis system for product testing based on the random forest model.

The random forest model uses a self-sampling method to generate multiple training subsets from the original dataset, which for product quality testing contains a large number of samples with quality parameters. By randomly sampling samples with put-back, the training subsets of each tree have different data distributions, and each training subset D_i is constructed in the following way:

$$D_i=\{x_k,y_k\},x_k\sim D,k=1,2,\cdots,N \tag{3}$$

where x_k is the sample feature vector, y_k is the corresponding category or numerical label, N is the number of samples, and the samples that have not been extracted are used as the validation set for subsequent model evaluation.

Next is the decision tree construction process, in the random forest model, the decision tree is formed by dividing the feature space layer by layer, each division is not based on all the features, but a subset is randomly selected from the total set of features, and the random forest model uses only a portion of the randomly selected features for splitting at each node. This random features can avoid overfitting and improve the generalization ability of the model, when splitting, the algorithm will choose the features that can make the largest change in the purity of the node, and the common index is the Gini index, which is calculated by the formula:

$$G(t) = 1 - \sum_{k=1}^{K} p_k^2 \tag{4}$$

where K is the number of categories, p_k is the proportion of samples belonging to the k th category. In product quality inspection, if the categories are "qualified" and "unqualified", the position where the Gini index decreases the most is the optimal splitting point, thus forming a binary decision structure, and after completing all the decision trees, the Random Forest Model integrates the outputs of all the trees to get the The final prediction result. In the product classification task, such as determining whether a batch of products is qualified or not, the model will use the majority voting method, i.e.:

$$\hat{y} = Mode\left\{T_1(x), T_2(x), \cdots, T_n(x)\right\} \tag{5}$$

where $T_i(x)$ is the prediction result of the i th decision tree.

In regression tasks, such as predicting the concentration of a chemical component of a product, the mean of the predicted values of all decision trees is used:

$$\hat{y} = \frac{1}{n}\sum_{i=1}^{n} T_i(x) \tag{6}$$

This integrated mechanism can effectively reduce the possible prediction errors of a single decision tree and improve the stability of the model.

Finally, the random forest model also has a built-in feature importance assessment function, which is particularly critical in product quality inspection. By calculating the contribution of each feature to the purity enhancement when splitting nodes in all trees, the variable that has the greatest impact on product quality can be identified, and the specific calculation formula is:

$$\mathrm{Im}\,por\tan ce\left(f\right) = \frac{1}{n}\sum_{i=1}^{n} \Delta G\left(T_i, f\right) \tag{7}$$

where $\Delta G(T_i, f)$ is the Gini index decrease value of feature f in the i th decision tree.

This feature can help product producers to clarify which production conditions (e.g., temperature, humidity) play a decisive role in product quality, so as to optimize the process and improve quality control.

II. C. Random forest model based product quality inspection system

II. C. 1) System architecture design

The architecture of the product quality inspection system consists of four modules: data acquisition, data storage and management, model calculation and result feedback, forming a complete process from raw data acquisition to quality assessment. The data acquisition module forms an IoT network through sensors such as DHT22 and PT124 to collect real-time production environment parameters, and at the same time obtains chemical composition and microbial data through ICP-MS and GC-MS, and transmits them to the edge gateway for preprocessing through the MQTT [19] protocol.

II. C. 2) Data acquisition and pre-processing design

In the data preprocessing section, the system analyzes the noise frequency components using Fast Fourier Transform (FFT) for the high-frequency sampled data from the environmental sensors and performs noise filtering through a low-pass filter design. For the collected chemical composition and microbial detection data, a standardized processing formula is used:

$$x' = \frac{x - \mu}{\sigma} \tag{8}$$

where x is the original data. μ and σ are the mean and standard deviation of the data, respectively.

To ensure that the data with different features are distributed within the same magnitude, the missing value processing part adopts the K Nearest Neighbor Interpolation (KNN) algorithm, in which the Euclidean distance formula is:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n}(x_{ik} - x_{jk})^2} \tag{9}$$

Missing values were filled in by finding the weighted mean of the nearest $k = 5$ data points.

Outlier rejection is performed using an outlier detection method based on the 3σ criterion, defined as $Outliers = \{x \,|\, |x - \mu| > 3\sigma\}$, which ensures the stability of the data by eliminating these outliers.

After the above preprocessing steps, all the data are integrated into a high-quality, structured dataset and stored in the HDFS distributed file system, which provides a reliable data base for the training and inference of the random forest model.

II. C. 3) Random Forest Model Construction and Training

The construction and training of the random forest model includes feature selection, model parameter setting and the specific implementation of the training process. In the feature selection stage, the correlation between the sample features (e.g., production temperature, humidity, pH) and the target variable (product quality score or pass rate) is analyzed using the Pearson correlation coefficient [20] with the formula:

$$\rho(X, Y) = \frac{Cov(X, Y)}{\sigma_X \sigma_Y} \tag{10}$$

At the same time, the recursive feature elimination (RFE) algorithm is applied to remove irrelevant features and retain the feature set that contributes most to the model prediction. The model construction stage uses the Scikit-learn framework to implement the random forest model, and the hyperparameters are set as follows: the number of trees is 150, the maximum tree depth is 30, and the minimum number of samples per node is 10; after the training set and test set are split, the model is constructed by using the training set, and the node division is optimized using the Gini exponent with Eq:

$$\Delta G = G_{parent} - \left(\frac{n_{left}}{n_{total}} G_{left} + \frac{n_{right}}{n_{total}} G_{right}\right) \tag{11}$$

Model training is implemented through multi-threaded parallel computation, and the accuracy and classification performance is evaluated using a test set upon completion.

III. Results of the product quality inspection system

III. A. Random Forest Model Prediction Results

In this experiment, Product A produced by a factory is selected as the research object, and 200 samples of the well-produced products are randomly selected as the samples for this experiment. The train_test_split module in the Scikit-learn library was used to divide 75% of the total samples into the training set and 25% into the test set before the training of the random forest model. The model was first trained using the training set and the corresponding parameters were optimized so that the robustness of the model could reach the best, and then it was tested on the test set, and the prediction results of the Support Vector Machine and Random Forest models are shown in Fig. 2 and Fig. 3, respectively. The red circular symbols in the scatter plot are the predicted values of the model for the test samples, and the green graphs are the true values of the test samples, we can judge the predictive ability of the model by their degree of overlap, and it can be seen from the figure that the predicted values in the Support Vector Machines often deviate from the true values. In contrast, the predicted values in the random forest model are almost identical to the true values. This shows that the random forest model is more suitable for product inspection than the support vector machine model.

After the model will be divided into training samples, the data of the training samples will first be unified for normalization, to eliminate the impact of experimental errors on model training, after the completion of the normalization process will be imported into the training samples of our model for training, at the same time, in order to further improve the predictive ability of the model, we use the grid search on the model parameters to do the tuning again, and finally determined the number of decision trees is 100, the The maximum depth of the decision tree is 20, and all other parameters are default parameters. After tuning, the final model prediction effect is shown in Figure 4, our test sample contains 0.1%-1.0%, 10 error gradients, in the figure the horizontal coordinate is the true error of our test sample, the vertical coordinate is the prediction error of our Random Forest algorithm model on the test sample. We fit the sample points in the graph, the solid line is the curve after fitting the sample, the closer the equation of the fitted curve is to y=x means the better the fit and the higher the model prediction accuracy. The prediction errors of the samples using the random forest model overlap well with the true errors of the measured samples.

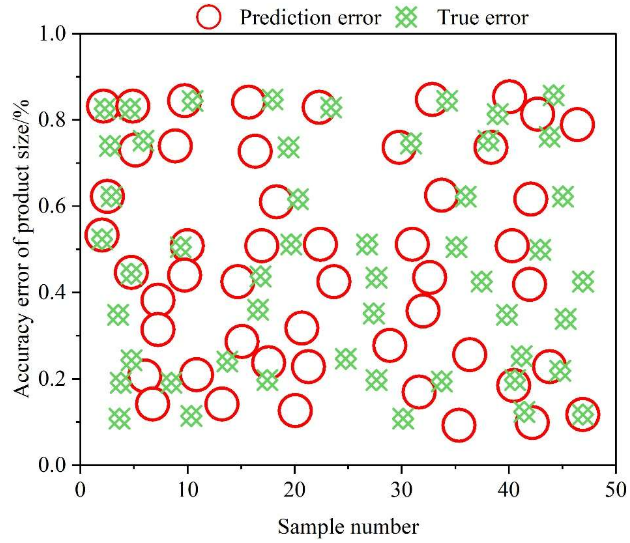

Figure 2: Support vector machine prediction results

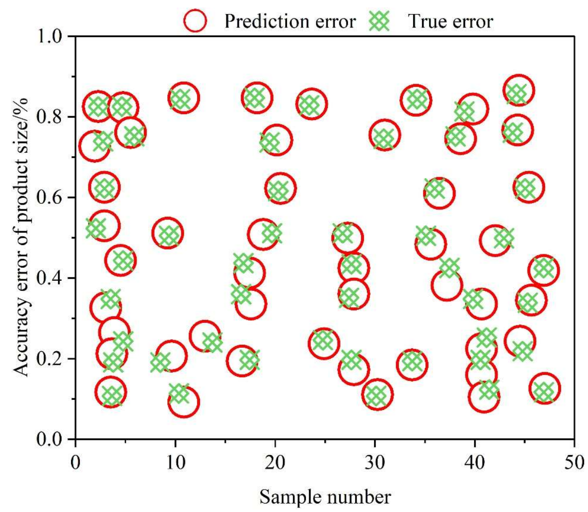

Figure 3: Prediction of random forest models

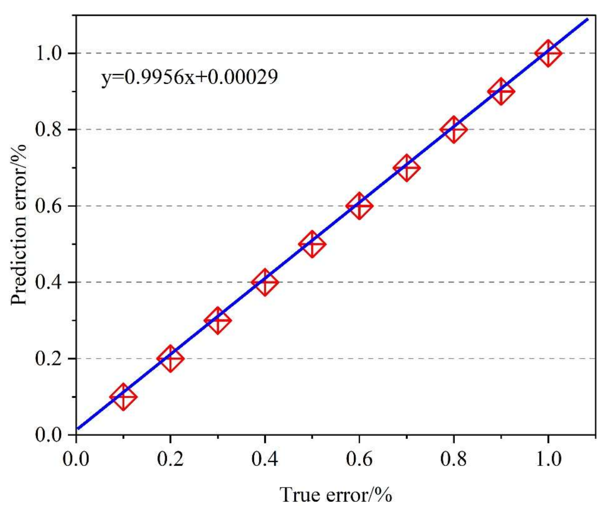

Figure 4: Final model prediction effect

In order to verify the usefulness of our model, we need to use this model to characterize other products in the market. We randomly selected products from ten factories and numbered them 1-10, respectively. The data of the products to be tested were imported into the prediction model, and the product production dimensional errors of the samples were determined using the model, and the final prediction results are shown in Table 1.

As can be seen from the results, our model on the product production dimensional error to go to the prediction results and the manufacturer's product production error of the permissible range of basically in line with the product production dimensional error is the maximum of 0.4%, are not beyond the permissible range of the error of the manufacturer's product production. This measurement directly demonstrates that our product quality inspection system combined with the Random Forest algorithm can realize the accurate inspection of product production quality.

Table 1: The predicted results of the random forest model

Sample number	Manufacturer	Permissible error range/%	Measuring error/%
1	A	0-0.4	0.1
2	B	0-0.6	0.2
3	C	0-0.7	0.1
4	D	0-0.9	0.3
5	E	0-0.8	0.4
6	F	0-0.7	0.1
7	G	0-0.2	0.1
8	H	0-0.3	0.2
9	I	0-0.5	0.4
10	J	0-0.6	0.1

III. B. Production line experimental validation

In order to more objectively verify the feasibility of the product quality inspection system based on the random forest model designed in this paper to promote new quality productivity, a series of comparative experiments were carried out. The experiments were carried out in a manufacturing enterprise, and 15 typical products were selected as processing objects. The experiments used an expert evaluation system based on the Delphi method to compare the comprehensive performance of the traditional factory production line and the automated production line under the Random Forest Model-based Product Quality Inspection System designed in this paper, in terms of five dimensions: production efficiency, processing quality, flexibilization level, intelligence level, and energy consumption level. Among them, production efficiency indicators include average beat time and comprehensive efficiency of equipment. Processing quality indicators include dimensional accuracy and surface roughness. Flexibility level indicators include production preparation time and product switching time. Intelligent level indicators include fault prediction accuracy and adaptive scheduling response time. The energy consumption level index includes the comprehensive energy consumption of a single product. The experimental process strictly follows the quality management standard AS9100D of aviation manufacturing industry, and adopts the DMAIC improvement process to ensure the reliability and consistency of the experimental data.

The experimental results are shown in Tables 2 and 3. As can be seen from the comparison results of production efficiency, the average beat time of the automated production line based on the system in this paper is 28.56% shorter than that of the traditional production line, and the comprehensive efficiency of the equipment has been improved by 12.9 percentage points to reach a high level of 91.5%. This is mainly due to the high-speed and high-precision data processing capability of the random forest model, which significantly improves the production beat time and equipment utilization. In terms of processing quality, the dimensional accuracy and surface roughness of the robotic automated production line reached 0.02mm and 0.7μm respectively, an order of magnitude higher than the traditional production line, meeting the demanding requirements of product manufacturing.

In terms of flexibility and intelligence, the automated production line based on the random forest model product quality inspection system also shows obvious advantages. The production preparation time was shortened from the traditional 130min to 18min, and the product switching time was shortened from 40min to 6min, which dramatically improved the response speed and flexibilization level of the production line. At the same time, the accuracy of fault prediction reaches more than 98%, and the response time of adaptive scheduling is shortened to less than 20s, which realizes the intelligent operation of the production line and promotes the further enhancement of the productivity of the new quality.

Table 2: The production efficiency is compared with the processing quality

Index	Conventional line	Automatic line	Optimized ratio
Mean time	125s	89.3s	-28.56%
Integrated equipment efficiency	78.6%	91.5%	+12.9 percentage points
Dimensional accuracy	0.4mm	0.02mm	It's 20 times higher
Surface roughness	6.5μm	0.7μm	It's 9 times higher

Table 3: Flexibility and intelligence level contrast

Index	Conventional line	Automatic line	Optimized ratio
Production preparation time	130min	18min	-86.15/%
Product switching time	40min	6min	-85.00/%
Failure prediction accuracy	-	98.54%	-
Dispatching response time	700s	18s	-97.14/%
Single product energy consumption	26.1kWh	15.2 kWh	-41.76/%

IV. Example analysis of new quality productivity improvement in enterprises

This part analyzes the indicators related to the promotion of new quality productivity by high-performance computing technology based on the product quality inspection system of the Random Forest Model, and selects three aspects of enterprise profitability, operating ability and development ability to evaluate the financial and economic level of the enterprise under the improvement of new quality productivity. By comparing the changes in financial indicators before and after the application of high-performance computing technology, the economic consequences of the application of high-performance computing technology in Enterprise A are analyzed.

IV. A. Horizontal Comparative Analysis of Enterprise Profitability

Table 4 shows the comparison of profitability indicators between enterprise A and the industry average, from 2013 to 2018, the profitability of the whole industry showed a downward trend, and only began to recover from 2019, and the development trend of enterprise A is consistent with the industry development trend. However, after Enterprise A implemented the high-performance computing technology of this paper in 2018, the gap with the industry gradually widened, and the situation of the indicators of the profitability of Enterprise A is significantly better than the average level of the industry, which indicates that the high-performance computing technology of this paper has a positive impact on the profitability of enterprises. Until 2024, the profitability of enterprise A has been much higher than the industry average, and its return on net assets is 16.97% higher than the industry average. This is enough to show that enterprise A carries out the high-performance computing technology of this paper can improve the profitability of the enterprise, even if the overall development of the industry is in a downturn, the enterprise through the high-performance computing technology of this paper to restore the profitability of the enterprise.

In summary, the high-performance computing technology of this paper has a positive effect on the profitability of enterprise A.

Table 4: Comparison of profitability indicators

Year	Sales margin/%		Asset returns/%		Return on equity/%	
	A company	Industry mean	A company	Industry mean	A company	Industry mean
2013	27.45	10.15	22.45	0.65	24.15	0.75
2014	24.56	10.58	21.56	2.65	24.56	3.98
2015	17.58	6.85	15.65	2.44	19.32	3.54
2016	8.45	6.85	6.54	2.65	8.56	3.54
2017	5.81	6.85	5.89	2.89	7.94	3.84
2018	2.65	6.85	3.56	-5.64	4.06	-6.21
2019	2.95	2.35	3.05	1.35	5.36	1.15
2020	5.36	3.24	7.56	263	9.44	3.06
2021	5.85	1.65	7.33	1.95	11.06	3.06
2022	5.33	2.68	7.15	2.11	9.84	3.19
2023	6.54	3.98	8.29	4.11	12.83	4.78
2024	11.25	7.25	13.59	3.98	23.56	6.59

IV. B. Horizontal Comparative Analysis of Enterprise Operating Capacity

Comparison of operating capacity indicators is shown in Table 5, from 2013 to 2017, enterprise A has not yet implemented the high-performance computing technology in this paper, and its inventory turnover ratio has been lower than the industry average, and there is no industry stability, indicating that enterprise A's inventory turnover is unstable, and it is easy to receive fluctuations due to the influence of the market and other factors.After 2018, enterprise A began to implement the high-performance computing technology in this paper, and the enterprise's Inventory turnover rate began to be higher than the industry average, and the trend of change with the industry shows different changes, A enterprise turnover rate overall is in an upward trend, but the industry is in an up and down fluctuation, until 2024, A enterprise's inventory turnover rate has been higher than the industry average, and the gap between the two is getting bigger and bigger, which indicates that A enterprise's inventory turnover speed is higher than the industry, and the more significant the advantages of inventory operation in the industry.

The overall description of enterprise A is the implementation of this paper's high-performance computing technology, its operating capacity performance is more stable, has been in an upward trend, and the more this paper's high-performance computing technology of the later part of the performance of the enterprise's operating capacity is better than the industry average, indicating that the enterprise to carry out this paper's high-performance computing technology to increase the competitiveness in the industry.

In summary, this paper's high-performance computing technology will have a positive impact on the operating capacity of enterprises, improve the market share of products, thereby increasing the sales revenue of enterprises to improve the operating capacity of enterprises, and this paper's high-performance computing technology on the inventory turnover rate of the enterprise has a more significant impact on the enterprise through this paper's high-performance computing technology to produce a better quality of the product, which contributes to the increase in the volume of enterprise product sales, and sales revenue increased. The enterprise produces better quality products through the high-performance computing technology in this paper, which leads to the increase of the sales volume of the enterprise.

Table 5: Comparison of operating ability indexes

Year	Receivable turnover (times)		Inventory turnover (times)		Total asset turnover/%	
	A company	Industry mean	A company	Industry mean	A company	Industry mean
2013	52.08	15.02	5.95	6.20	0.87	0.60
2014	68.66	13.44	5.17	6.41	0.86	0.68
2015	72.69	13.43	3.87	6.40	0.8	0.68
2016	73.17	13.38	4.20	6.36	0.77	0.81
2017	67.18	13.85	5.49	6.44	0.86	0.83
2018	71.01	12.27	6.42	6.26	0.89	0.78
2019	95.69	9.35	6.10	5.52	0.95	0.82
2020	91.10	10.31	7.09	5.23	1.05	0.85
2021	92.08	10.58	7.81	5.45	1.09	0.76
2022	139.31	11.64	8.79	5.32	1.14	0.81
2023	164.42	13.76	9.15	6.38	1.14	0.31
2024	125.49	14.14	10.13	7.54	1.14	0.47

IV. C. Horizontal Comparative Analysis of Enterprise Development Capability

Comparison of development capacity indicators is shown in Table 6, from 2013 to 2018, in terms of operating income growth rate, the overall industry average is in a state of decline, the trend of change of the enterprise is basically the same as the industry in the first few years, and has been higher than the industry average, but in 2016 it was lower than the industry average. In 2019 and beyond, the industry's operating income growth rate began to rebound, but has been fluctuating and lower growth rate, but the trend of changes in the growth rate of enterprise A is the same as the industry, but the growth rate is significantly better than the industry performance, indicating that the enterprise's profitability is at the forefront of the industry. 2018 to 2024, enterprise A is below the industry average again in 2018 and 2020, respectively. However, the enterprise years are all higher than the industry performance and much higher than the industry average, indicating that enterprise A's asset size growth is very good and strong development ability.

In summary, after the implementation of the high-performance computing technology in this paper, the development ability of the enterprise is gradually enhanced, and there is no more negative growth rate, and it is much higher than the industry average.Enterprise A improves the visibility of the enterprise through the high-performance computing technology in this paper, and utilizes the high-performance computing technology to reduce the cost of production, and produces the products to improve the competitiveness of the enterprise's brand, and increases the market share, and increases the operating income of the enterprise. Increase the business income of the enterprise, and the enterprise also expands the asset scale and enhances the ability of capital accumulation as a result.

Table 6: The comparison of development ability indexes

Year	Revenue growth/%		Total asset growth rate/%		Rate of operating profit/%	
	A company	Industry mean	A company	Industry mean	A company	Industry mean
2013	34.16	20.15	12.54	9.54	59.45	23.54
2014	39.56	19.54	36.56	8.65	20.65	15.65
2015	21.56	17.56	28.95	8.65	-10.41	7.56
2016	2.89	17.56	-0.69	8.65	-56.54	7.56
2017	18.26	15.45	12.56	8.65	-13.56	8.54
2018	26.54	-18.56	11.63	16.45	-45.45	-15.64
2019	6.23	1.15	6.56	5.64	18.78	-0.89
2020	19.36	8.54	0.12	5.89	117.89	5.44
2021	12.45	4.56	26.54	5.64	22.56	-1.51
2022	28.56	4.95	9.78	4.56	17.88	4.32
2023	26.54	2.56	47.56	0.78	55.97	5.98
2024	31.26	2.55	14.56	5.98	123.56	19.89

V. Paths of economic policy innovation based on the needs of new quality productivity

V. A. Optimizing the design of tax incentives

With the rise of emerging industries and the transformation and upgrading of traditional industries, new productive forces are growing rapidly, and tax incentives need to be more industry-oriented according to the key areas and key links in the development of new productive forces. Fiscal policies should give key support to strategic emerging industries, such as new energy, new materials, biomedicine, etc., and provide reductions or preferential tax rates for enterprise income tax and value-added tax, so as to help the rapid growth of emerging industries. For frontier technology fields such as artificial intelligence, quantum information, integrated circuits, etc., special tax incentive programs can be set up, and enterprises engaged in related R&D and production can be given greater tax exemptions and reductions, so as to encourage enterprises to increase their investment in these fields, and to promote the cultivation and development of new productive forces. At the same time, appropriate tax incentives should also be given to traditional industries that are actively using new technologies for transformation and upgrading in order to promote the overall optimization of the industrial structure.

V. B. Adjusting the structure of financial investment in science and technology

To optimize the structure of financial investment in science and technology, the first and foremost task is to make the direction of financial investment closely match national strategies and industrial development needs. On the one hand, the Government needs to give sustained and high-intensity financial support to key scientific and technological fields that have a bearing on national security and long-term development, such as artificial intelligence, quantum science and technology, aerospace and other fields. Research in these fields is characterized by a long cycle, high risk and high investment, and it is difficult to attract sufficient resources if we rely only on the market mechanism, so the guidance of financial funds is crucial. Through stable financial investment, the government can gather top scientific research talents to overcome core technical problems, so as to enhance the country's right to speak in the global scientific and technological competition. On the other hand, focusing on the scientific and technological needs of the transformation and upgrading of traditional industries, the government should increase financial investment in areas such as green energy and new materials.

V. C. Enhancing synergies in industrial support policies

Establishing a coordination mechanism for tax incentives to strengthen coordination between different departments and avoid policy overlap and conflict. For example, a cross-departmental industrial policy coordination leading group or a joint meeting system can be set up to study and solve problems arising in the implementation of industrial support policies. Alternatively, a unified industrial support policy plan and implementation program could be formulated, with a clear division of responsibilities among various departments to ensure that policy objectives are consistent and policy measures are mutually supportive.

VI. Conclusion

The application of high-performance computing technology in the field of product quality inspection shows significant economic benefits and social value. By constructing a product quality inspection system based on the random forest model and conducting empirical research, it is confirmed that this technology plays an important role in promoting the enterprise's new quality productivity improvement. The experimental results show that after applying the system, the productivity is significantly improved, the average beat time is reduced from 125 seconds to 89.3 seconds, and the comprehensive efficiency of the equipment is improved by 12.9 percentage points to 91.5%. In terms of long-term benefits, Enterprise A's economic indicators continue to improve after the implementation of this technology, with a growth rate of 31.26% in revenue in 2024, much higher than the industry average of 2.55%. These results validate the potential of HPC technology in reducing production costs, improving product quality and optimizing business operations.

Based on the research findings, economic policy innovation should focus on three directions: first, optimize the design of tax incentives, and provide differentiated tax support for strategic emerging industries and cutting-edge technologies; second, adjust the structure of financial investment in science and technology, and increase the sustained support for key scientific and technological areas; and third, enhance the synergies of industrial support policies, and establish a cross-sectoral coordination mechanism to ensure that the policies and measures are mutually reinforcing. These policy innovations will create a favorable environment for the widespread application of high-performance computing technology and promote the optimization of industrial structure and high-quality economic development. Future research could further explore the economic effects of the integration and application of high-performance computing and other emerging technologies, as well as more precise policy support paths.

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