Research on Optimization Path of Enterprise Cost Management under Intelligent Accounting Environment

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ABSTRACT Enterprise cost management in intelligent accounting environments requires integrated data processing, dynamic accounting, predictive control, and decision support. Traditional cost-management models suffer from fragmented data, rigid allocation rules, and weak real-time control capability. This study proposes a systematic optimization path for enterprise cost management based on multi-source data standardization, activity-based costing, regression-based cost-driver identification, machine-learning prediction, and dynamic feedback control. First, heterogeneous cost data are integrated, cleaned, and standardized to form a unified multidimensional cost dataset. Second, an intelligent activity-based costing model dynamically allocates resource costs to activities and cost objects according to observed driver variables. Third, machine-learning regression models predict future costs and identify deviations through standardized residuals, enabling rolling adjustment and early warning. Finally, multidimensional cost analysis and scenario-based optimization are used to support resource allocation decisions. Experiments using monthly cost data from manufacturing enterprises show that the proposed method reduces MSE to 58.73, MAE to 5.42, and the cost deviation rate to 0.051, outperforming traditional accounting, non-intelligent ABC, and machine-learning models without feedback adjustment. The method provides a data-driven framework for intelligent cost prediction, time-series control, and enterprise decision support.

INDEX TERMS intelligent accounting, activity-based costing, machine learning, time-series prediction, cost control

I. INTRODUCTION

As the digital transformation of enterprises and intelligent financial systems keeps growing, the cost management process is slowly altering between the traditional accounting models to data-driven ones. Nevertheless, in practice, the enterprise cost management continues to experience such issues as the spread of data across various sources, the lack of uniformity in data definitions, and the slow processing of information, which leads to the inability to provide accurate cost accounting and support decision making. Simultaneously, the conventional cost allocation models are based on the fixed rules, and they fail to reflect the relationships of resources consumption in the complex companies operations; on the cost control level, no effective forecasting and dynamic adjusting mechanisms allow the cost management to remain at the stage of the postevent analysis, and it is hard to respond to the cost changes promptly [1-3].

In a bid to mitigate the above problems, this paper develops an optimization path system in enterprise cost management in an intelligent accounting environment. The data level ensures that multi-source cost data integration and standard processing approach result in a single data representation and quality input. On the accounting level, an intelligent accounting model is constructed using activity-based costing (ABC), and data analysis techniques are merged to identify the main cost drivers and optimize the cost allocation mechanisms. At the control level cost prediction using machine learning models is proposed and deviation identification and feedback adjustment are used in dynamic control. A multi-dimensional cost analysis and optimization model is developed at the decision making level to offer data-driven cost decision support.

II. RELATED WORK

With the background of enterprise digital and smart transformation, artificial intelligence and data-driven technologies are slowly infiltrating every sphere of the enterprise management and information systems. Similar studies have been conducted at various levels such as database management, business process optimization, enterprise level data processing and decision support, displaying a trend of development toward the optimization of data processing at the enterprise level towards an intelligent decision-driven approach. To begin with, regarding the underlying data and system support, Oloruntoba suggested an autonomous database management system founded on artificial intelligence according to the database management. It could use machine learning and automation processes to achieve self-tuning, query optimization and index management, thus enhancing the performance of the system and minimising the operation and maintenance expenses [4]. This paper focuses on smart upgrading of data processing infrastructure and offers effective support of further data analysis and usage. Along with this, Machireddy also discussed the data quality and performance optimization challenges of ETL process in the aspect of data engineering. He noted that in the distributed and hybrid processing mode, there is need to balance the accuracy and processing efficiency, and to enhance the overall system performance based on parallel computing and schedule resources, and to enhance the data governance and metadata management. The two studies representing the different levels express that the prerequisites of intelligent applications realization are high-quality data processing and high-performance system architecture.

On this basis, the study has gradually been expanded to business process and enterprise application layer. Nittala has offered an ERP process mining and optimization model which incorporates artificial intelligence. It achieves process visualization and bottleneck identification using event log analysis and task mining and optimizes business processes dynamically with a combination of machine learning, causal inference and reinforcement learning. At the same time, it generates improvement solutions with the help of large language models, which effectively improves the efficiency of enterprise operation and reduces risks [5]. Antwi and Avickson began with the use of enterprise resource management systems (including SAP) to examine the aspect of artificial intelligence in data analysis, process automation and decision optimization, noting that it can greatly enhance the efficiency of supply chain, customer relationship and resource allocation and make business processes intelligent and personalized [6]. Moreover, Mathur created a machine learning risk prediction platform in the medical big data scenario in real time. It achieves effective data processing and risk alert using streaming computing and deep learning models, and provides a system to enhance system reliability by model update and interpretability mechanisms [7]. This paper confirmed the prediction and decision value of data-driven models in complex environments at the application layer. Meanwhile, as far as enterprise architecture is concerned, as Hindarto notes, analyzing the organizational structure and business processes in a holistic manner, it is possible to increase the efficiency of resource allocation and precision of decision-making, as well as increase the adaptability and scalability of the system.

Overall, although the current literature has touched upon many aspects of it, such as the data infrastructure, optimization of processes, and intelligent decision-making, it still has a tendency toward the general trait of a layered development and the absence of the synergy between the underlying data processing, process optimization, and decision support. Thus, an integrated cost management optimization system has to be built that crosses between the fields of data processing, cost accounting, predictive control and decision support in an intelligent accounting environment to have synergistic integration and value addition among various technologies.

III. METHODS

A. INTELLIGENT PROCESSING PATH FOR COST DATA

1) Multi-source cost data integration and cleaning mechanism

This maps multi-source data to a unified data space. Let the cost data in the (i)th data source be Ci, then the integrated cost dataset can be represented as:

$$C = \bigcup_{i=1}^{n} \phi_i(C_i) \tag{1}$$

Here, $\phi_i(\cdot)$ represents a function that performs field mapping and format conversion for different data sources.

During the data cleaning phase, to reduce the interference of outliers and noise on cost analysis, anomaly detection methods based on statistical characteristics can be used. Let the cost data sequence be $(x_1, x_2, ..., x_n)$, with mean and standard deviation and respectively μ, σ. Then the criteria for determining outliers are:

$$|x_i - \mu| > k\sigma \tag{2}$$

Where k is the threshold coefficient (usually 2 or 3). By removing or correcting outlier data, the accuracy and consistency of cost data can be significantly improved. Furthermore, combining automated scripts with ETL processes enables batch and real-time data cleaning, improving overall processing efficiency.

2) Cost Data Standardization and Structured Processing Methods

After data integration and cleaning, cost data needs to be standardized and structured to eliminate dimensional differences and improve data comparability. A common method is range standardization, whose expression is:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

Where x_i' is the standardized data value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values in the sample, respectively. This method can uniformly map cost indicators of different dimensions to the [0, 1] interval, which is beneficial for subsequent model calculations.

In terms of structured processing, multidimensional data models can be constructed based on cost objects and cost drivers. Let the total enterprise cost be C, which can be decomposed into a weighted combination of multiple cost drivers:

$$C = \sum_{j=1}^{m} w_j f_j \tag{4}$$

Here, f_j represents the jth cost driver (such as labor, materials, equipment, etc.), and w_j represents the corresponding weight. By transforming unstructured or semi-structured data into this multidimensional structure, the cost data can be calculable and modeled.

B. INTELLIGENT OPTIMIZATION PATH FOR COST ACCOUNTING

1) Construction of Intelligent Accounting Model Based on Activity-Based Costing

Activity-based costing (ABC) uses the "resource-activity-cost object" path as its core to rationally allocate indirect costs through activity activities. In an intelligent environment, data mining and automatic identification technologies can be used to dynamically model activity activities. Let the total resource cost of the enterprise be R, and the set of activities be A = a_1, a_2, ..., a_m, then the resource cost allocated to the jth activity is:

$$C_{aj} = R \times \frac{d_j}{\sum_{k=1}^{m} d_k} \tag{5}$$

Among them, d_j represents the resource consumption driver of activity a_j (such as working hours, machine running time, etc.). Furthermore, activity costs are allocated to cost objects (such as products or services). Let the set of cost objects be $O = \{o_1, o_2, \ldots, o_n\}$, then the total cost of the ith cost object can be expressed as:

$$C_{oi} = \sum_{j=1}^{m} C_{aj} \times \frac{u_{ij}}{\sum_{l=1}^{n} u_{lj}} \tag{6}$$

Here, u_{ij} represents the amount of consumption of the cost object o_i by the activity a_j.

2) Cost Driver Identification and Dynamic Allocation Mechanism Optimization

Accurate identification of cost drivers is crucial for improving accounting quality. In an intelligent accounting environment, cost drivers can be identified through data-driven methods based on correlation analysis or regression models. Let $(x_1, x_2, \ldots, x_p)$ be multiple potential driver variables. The relationship between cost C and these variables can be expressed as:

$$C = \beta_0 + \sum_{k=1}^{p} \beta_k x_k + \epsilon \tag{7}$$

Where β_k represents the influence coefficient of each driver, and ϵ represents the random error term. Through parameter estimation and significance testing, key cost drivers can be identified, improving the model's interpretability.

Based on this, a dynamic cost allocation mechanism is constructed. Let the weight of a certain cost driver in period t be $w_j^{(t)}$, then it can be adjusted using a time update function:

$$w_j^{(t)} = \frac{x_j^{(t)}}{\sum_{k=1}^{m} x_k^{(t)}} \tag{8}$$

Wherein, $x_j^{(t)}$ represents the actual observed value of driver j in period t. This method can adjust the cost allocation ratio in real time according to business changes, avoiding the deviation problem caused by the traditional fixed allocation rate.

In addition, a feedback adjustment mechanism is introduced to correct errors in the accounting results. Let the actual cost be C^{real} and the predicted or allocated cost be C^{est}, then the deviation is:

$$\Delta C = C^{\text{real}} - C^{\text{est}} \tag{9}$$

By continuously tracking deviations and adjusting parameters, the weights of driving factors and allocation rules can be continuously optimized, achieving adaptive optimization of cost accounting.

C. COST FORECASTING AND CONTROL OPTIMIZATION PATH

1) Machine Learning-Based Cost Prediction Methods

The core of cost forecasting lies in depicting the mapping relationship between historical data and future costs. Based on machine learning methods, nonlinear forecasting models can be constructed to improve forecast accuracy. Let the historical feature variable be X= (x_1, x_2, ..., x_n) and the corresponding cost be C, then the forecasting model can be expressed as:

$$\hat{C} = f(X; \theta) \tag{10}$$

Where f(·) is the regression model, $\theta$and are the model parameters.

During model training, parameter optimization is achieved by minimizing the loss function. A commonly used mean squared error loss function is:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^{N} \left(C_i - \hat{C}_i \right)^2 \tag{11}$$

Where N represents the number of samples. Optimal parameters θ^* can be obtained through iterative optimization, thereby improving the fitting ability of the prediction results.

Furthermore, to enhance the model's ability to characterize time series features, lagged variables can be introduced to construct a dynamic prediction model. For example, using the costs of the previous k periods as input, we have:

$$\hat{C}_t = f(C_{t-1}, C_{t-2}, \ldots, C_{t-k}) \tag{12}$$

This method can capture the temporal dependence of cost changes and improve the ability to identify cyclical and trend fluctuations, thereby providing data support for enterprise budgeting and resource allocation.

2) Cost Deviation Identification and Dynamic Control Mechanism

Based on cost forecasting, a deviation identification and dynamic control mechanism needs to be further constructed to achieve real-time monitoring of cost fluctuations. Let the actual cost in period t be C_t and the predicted cost be $\hat{C}_t$, then the cost deviation is defined as:

$$e_t = C_t - \hat{C}_t \tag{13}$$

To determine whether the deviation is abnormal, standardization can be introduced:

$$z_t = \frac{e_t - \mu_e}{\sigma_e} \tag{14}$$

Where μ_e and σ_e are the mean and standard deviation of the historical deviation, respectively. When $|z_t| > \delta$ (the threshold) is reached, it can be identified as an abnormal deviation and an early warning mechanism can be triggered.

In terms of dynamic control, a control model based on feedback adjustment can be constructed. Let the control adjustment be u_t, then the corrected cost control value is:

$$C_t^{\mathrm{adj}} = \hat{C}_t + u_t \tag{15}$$

This u_t can be dynamically adjusted based on the deviation, for example, by using a proportional adjustment strategy:

$$u_t = -\lambda e_t \tag{16}$$

Wherein, λ is the adjustment coefficient. This mechanism can promptly correct cost control strategies when deviations occur, suppressing the trend of cost overruns.

By further integrating a rolling forecasting mechanism, a closed-loop process of "prediction - deviation identification - dynamic adjustment" is achieved through continuous updates to model inputs and parameters, thereby improving the real-time performance and adaptability of cost control.

D. COST DECISION SUPPORT OPTIMIZATION PATH

1) Construction of Multidimensional Cost Analysis Model

To comprehensively reflect the cost structure and its influencing factors, a multidimensional cost analysis model needs to be constructed to decompose and characterize cost information across multiple dimensions. Let the total cost of the enterprise be C, which can be decomposed from the time, business, and resource dimensions:

$$C = \sum_{t=1}^{T} \sum_{i=1}^{n} \sum_{j=1}^{m} C_{tij} \tag{17}$$

Here, C_{tij} represents the cost composition under time period t, business type i, and resource type j. This model enables fine-grained cost breakdown, which helps identify key cost drivers.

Based on this, a contribution analysis method is introduced to evaluate the impact of each dimension of factors on the total cost. Let the contribution of the jth factor be:

$$\eta_j = \frac{C_j}{C} \tag{18}$$

Here, C_j represents the cost component corresponding to this factor. By analyzing the ranking of η_j, the main cost sources can be identified, enabling precise positioning of key cost elements.

Furthermore, dimensionality reduction methods (such as principal component analysis) can be used to compress and represent multidimensional data. Let the original variable vector be X, then it can be transformed into:

$$Z = W^T X \tag{19}$$

Where W is the transformation matrix, and Z is a low-dimensional representation. This method can reduce analytical complexity and improve decision analysis efficiency while preserving key information.

2) Data-Driven Cost Decision Optimization Method

Based on multidimensional analysis, a cost decision optimization model can be further constructed, unifying the cost control objective with resource constraints. Let the firm's decision variables be x= (x_1, x_2, ..., x_n) and the corresponding cost function be C(x) , then the cost-optimal decision problem can be expressed as:

$$\min_x C(x) \tag{20}$$

$$\text{s.t.} \quad g_k(x) \leq b_k, \quad k = 1, 2, \ldots, K \tag{21}$$

Among them, gk(x) represents resource constraints (such as budget, production capacity, etc.), bkwhich is the upper limit of the constraint.

To improve the model's real-world adaptability, a data-driven parameter update mechanism can be introduced. Let the model parameters be θ, then they are continuously updated using historical data:

$$\theta^{(t+1)} = \theta^{(t)} + \alpha \nabla L\left(\theta^{(t)}\right) \tag{22}$$

Where $\alpha$is the learning rate and L(θ) is the loss function. This process enables the decision model to continuously optimize according to changes in the environment.

Furthermore, scenario analysis methods can be used to evaluate different decision-making options. Let the cost of scenario sbe C(s) , and its probability of occurrence be p_s, then the expected cost is:

$$E(C) = \sum_{s=1}^{S} p_s C(s) \tag{23}$$

By comparing the expected costs and risk levels of different options, the optimal decision path can be selected.

IV. RESULTS AND DISCUSSION

A. DATASET CONSTRUCTION AND SAMPLE SPLITTING

We selected actual business data from three large-scale manufacturing enterprises in the and goods sector as the basic sample. The dataset covers a continuous 10-year period from 2014 to 2023, comprising 120 monthly observation points for each enterprise (Total N = 600). The data was split using a time series method, where the first 84 months (70%) served as the training set and the remaining 36 months (30%) as the test set. To ensure robustness, the model explicitly accounts for seasonal fluctuations and long-term industry trends within the cost data. To ensure the temporal characteristics and completeness of the data, the raw data was organized in chronological order, and a cost analysis dataset was constructed $D = (X_i, C_i)_{i=1}^{N}$, where X_i represents multi-dimensional feature variables and C_i represents the corresponding cost values. The data was split using a time series method, with the first 70% of the samples used as the training set and the last 30% used as the test set, to ensure the realism and generalization ability of the model evaluation.

B. COMPARISON MODEL AND EXPERIMENTAL SETUP

To verify the effectiveness of the constructed optimization path, the following comparison methods were set up:

(1) traditional cost accounting method (based on fixed allocation rate);

(2) a standard, non-intelligent Activity-Based Costing (ABC) model to serve as a rigorous baseline for allocation accuracy;

(3) an integrated machine learning prediction model lacking the dynamic adjustment feedback loop;

(4) the comprehensive optimization path method proposed in this paper.

During the experiments, a unified parameter initialization strategy and data input format were used to ensure comparability between different methods. Model training employed an iterative optimization approach until the loss function converged.

C. EVALUATION INDEX SYSTEM

Evaluation indicators are constructed from two aspects: prediction accuracy and control effectiveness.

(1) Prediction accuracy index:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(C_i - \hat{C}_i\right)^2 \tag{24}$$

The model's predictive ability is measured by mean square error and mean absolute error.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|C_i - \hat{C}_i\right| \tag{25}$$

(2) Cost control effectiveness indicators: The Mean Cost Deviation Rate (δ) is employed to measure global control capability, defined as the average of the absolute percentage errors across all test samples:

$$\delta = \frac{1}{n}\sum_{i=1}^{n}\frac{|C_{\mathrm{real},i} - C_{\mathrm{est},i}|}{C_{\mathrm{real},i}} \tag{26}$$

To ensure the scientific validity of the improvements, independent samples t-tests were conducted, confirming that the reduction in MSE and deviation rates for the proposed method is statistically significant at the $p < 0.01$ level compared to the traditional ABC baseline.

(3) Stability indicators: Stability is controlled by assessing the standard deviation of cost fluctuations.

$$\sigma_C = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(C_i - \bar{C}\right)^2} \tag{27}$$

Wherein, $\bar{C}$ represents the average cost level.

TABLE 1. Comparison of cost prediction accuracy under different methods

Method	MSE	MAE	Deviation Rate (δ)
Traditional Cost Accounting Method	185.32	10.84	0.128
Single Cost-Driver Model	121.45	8.15	0.091
Machine Learning Prediction (Without Dynamic Adjustment)	96.45	7.18	0.082
Proposed Method	58.73	5.42	0.051

Table 1 shows that different methods exhibit significant differences in cost forecasting accuracy. The proposed method, by integrating multi-source data processing, activity-based costing (ABC), and dynamic control mechanisms, further optimizes forecasting performance, reducing MSE and MAE to 58.73 and 5.42, respectively, and the bias rate to 0.051, representing reductions of approximately 68.3%, 50.0%, and 60.2% compared to traditional methods. The results demonstrate that the proposed optimization path effectively improves the accuracy and stability of cost forecasting, providing strong support for enterprises to implement refined cost management.

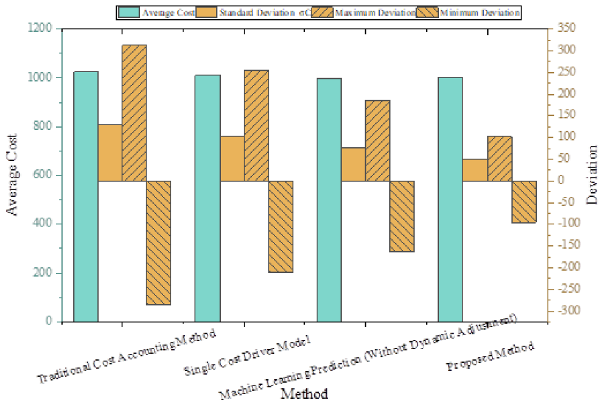

FIGURE 1. Comparison of cost control stability under different methods

The difference between the stability of different methods in controlling cost is presented in figure 1. By combining multidimensional data modeling and dynamic control mechanisms, the approach described in this paper demonstrates a better stability performance. Its standard deviation is also smaller by 48.9, which is about 62.0 % less than the traditional approaches. The upper and lower deviation are brought to 102.6 and -95.3 respectively, which means that the range of fluctuations has been narrowed down. At the same time, its mean price of 1002.1 is more in line with a reasonable range than other approaches, which proves that this approach does not cause systematic bias whilst reducing variations. To conclude, the approach discussed in this paper is an efficient way of decreasing the variability of costs and increasing the stability of control, which proves its benefits in cost management that is dynamic.

V. CONCLUSION

In this paper, the optimization of cost management within an intelligent accounting environment is developed, and a systematic path would be created, which would include the cost data processing, accounting optimization, predictive control, and decision support. It enhances the quality of data by integrating and standardizing multi-source data, to realize fined cost accounting by activity-based costing and data analysis techniques, and incorporates machine learning and dynamic feedback functions to improve cost prediction and control. Moreover, it integrates the multi-dimensional analysis and optimization models to enhance the scientific character of the decision-making. The experimental results indicate that the proposed approach is much better than the comparative approaches in terms of predicting costs accurately and maintaining control, which is an effective way to reduce the error in prediction and costs, and therefore the practicability and usefulness of this optimization direction is verified. It is necessary to add that this study has some limitations, including the insufficient size of experimental evidence and industry coverage, and the necessity to prove once again its applicability to real-life complex situations. Future studies can expand the model into larger, more multi-industrial-level data setting and integrate deep learning and reinforcement learning to enhance the adaptive capability and intelligent level of decision-making of the cost management.

AUTHOR CONTRIBUTIONS

Conceptualization –Jinfeng Dong and Xin Zhang; methodology – Jinfeng Dong and Xin Zhang; investigation – Jinfeng Dong and Xin Zhang; writing-original draft preparation – Jinfeng Dong and Xin Zhang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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REFERENCES

[1] B. O. Antwi and E. K. Avickson, “Integrating SAP, AI, and data analytics for advanced enterprise management,” International Journal of Research Publication and Reviews, vol. 5, no. 10, pp. 621-636, 2024, doi: 10.55248/gengpi.5.1024.2722.

[2] J. R. Machireddy, “Data quality management and performance optimization for enterprise-scale etl pipelines in modern analytical ecosystems,” Journal of Data Science, Predictive Analytics, and Big Data Applications, vol. 8, no. 7, pp. 1-26, 2023.

[3] P. K. Kaulwar, A. Pamisetty, S. Mashetty, et al., “Harnessing Intelligent Systems and Secure Digital Infrastructure for Optimizing Housing Finance, Risk Mitigation, and Enterprise Supply Networks,” International Journal of Finance (IJFIN)-ABDC Journal Quality List, vol. 36, no. 6, pp. 372-402, 2023.

[4] N. O. Oloruntoba, “AI-Driven autonomous database management: Self-tuning, predictive query optimization, and intelligent indexing in enterprise it environments,” World Journal of Advanced Research and Reviews, vol. 25, no. 2, pp. 1558-1580, 2025, doi: 10.30574/wjarr.2025.25.2.0534.

[5] E. P. Nittala, “AI-Powered ERP Process Mining and Optimization Techniques for Agile Enterprise Transformation,” American International Journal of Computer Science and Technology, vol. 7, no. 6, pp. 15-24, 2025, doi: 10.63282/3117-5481/AIJCST-V7I6P102.

[6] M. Mathur, “Real Time Big Data AI Engine for Enterprise Healthcare Risk Prediction with Streaming Analytics Optimization,” International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), vol. 9, no. 1, pp. 154-163, 2026.

[7] D. Hindarto, “The management of projects is improved through enterprise architecture on project management application systems,” International Journal Software Engineering and Computer Science (IJSECS), vol. 3, no. 2, pp. 151-161, 2023, doi: 10.35870/ijsecs.v3i2.1512.