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Design and Implementation of ABC Intelligent Accounting System for Manufacturing Industry

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ABSTRACT With the deep integration of intelligent manufacturing and digital transformation, manufacturing production is moving toward multi-variety, small-batch, and customized modes, increasing the proportion of indirect costs in total cost. Traditional cost accounting based on a single allocation standard can no longer meet refined cost-management requirements. To solve problems in Activity-Based Costing application, including difficult data collection, unclear activity-center division, low accounting efficiency, and weak real-time performance, this paper designs and implements an ABC intelligent accounting system for manufacturing enterprises. First, an overall system architecture is constructed based on manufacturing production characteristics and ABC accounting logic. Second, key modules including data collection, activity-center division, and cost allocation are designed, and artificial intelligence algorithms are introduced to optimize cost-driver identification and allocation efficiency. Finally, a large manufacturing enterprise is used for system testing. Results show that the system supports automated collection of multi-source cost data with collection delay below 5 minutes, reducing manual recording delay by 90%. Cost accounting time for a single production batch is reduced from 8 hours to 30 minutes, providing reliable support for refined manufacturing cost management.

INDEX TERMS activity-based costing, intelligent accounting, manufacturing industry, cost driver analysis, data integration

I. INTRODUCTION

In the context of global economic integration and increasingly fierce market competition, cost management has become the core link of manufacturing enterprise management, and refined cost accounting is the key to enhancing the core competitiveness of enterprises. With the rapid development of intelligent manufacturing, the production processes of manufacturing enterprises are becoming increasingly complex, and the types of products are constantly enriching. The proportion of indirect costs such as equipment depreciation, energy consumption, and management expenses in the total cost continues to increase. The traditional accounting method of allocating indirect costs based on single indicators such as output and working hours has the drawback of rough allocation, which can easily lead to distortion of product cost information, thereby affecting the scientificity of enterprise product pricing, production planning, and resource allocation decisions. The activity-based costing method takes “homework” as its core and allocates costs based on the resource consumption of homework, which can effectively compensate for the shortcomings of traditional cost accounting methods and achieve more accurate cost accounting. However, in the actual application process of manufacturing, ABC faces many constraints such as tedious manual operations, difficulties in data integration, and low efficiency, which restrict its promotion and application. Therefore, designing an ABC intelligent accounting system for the manufacturing industry, improving the efficiency and accuracy of cost accounting, and promoting refined management of enterprises, has important theoretical and practical significance [1,2].

The main contributions of this article are reflected in three aspects: firstly, combining the production characteristics of manufacturing industry, deeply integrating ABC theory with intelligent technology, breaking through the bottleneck of traditional ABC relying on manual operation, and realizing the intelligence of the entire process from data collection to cost allocation and report output; The second is to optimize key processes such as task center division and cost driver identification, introduce machine learning algorithms to automatically identify key cost drivers, and improve the rationality and accuracy of cost allocation; Thirdly, the system architecture demonstrates potential scalability and compatibility for various manufacturing frameworks. While its current implementation relies on existing digital infrastructure—leading to lower adaptation rates in less digitized environments—the modular design provides a technical blueprint for the broader promotion and application of ABC in the manufacturing industry as digital transformation matures.

The structure of this article is as follows: The second part analyzes the problems and challenges faced by ABC in manufacturing applications; The third part elaborates on the design method of intelligent accounting system; The fourth part validates the system through experiments and discusses the results; The fifth part summarizes the entire text and provides prospects for future research [3,4].

II. PROBLEMS AND CHALLENGES

Prominent data collection and integration problems faced by ABC in manufacturing are the current main constraint to the development of ABC. Manufacturing production consists of procurement, production, warehousing and sales. Cost data is distributedly existing in different information systems, such as enterprise resource planning system, production management system and IoT monitoring system, and forms the information island. Traditional ABC data collection method is manual input, which not only causes a large amount of financial personnel work and effort, but also causes data error and delay because of the large amount and diverse types of data. For example, in the multi variety and small batch production mode, the raw material consumption, equipment usage time, labor for each product and operation should be tracked and collected. It is difficult for the manual data collection method to meet the requirements of real-time and accurate data, which will directly affect the effect of cost accounting [5,6].

The other significant challenge involves the imprecise demarcation of activity centers and the subsequent inefficiency in cost allocation. Scientific division of work centers is the premise of the application of ABC. Many manufacturing enterprises lack clear standard and method in the division of work centers in the division process, which leads to the division of work centers too general or too detailed. Too general division of work centers will cause inaccurate cost allocation, and too detailed division of work centers will cause the problem of excessive division and increasing management cost, and affect the effect of cost accounting. At the same time, traditional ABC cost allocation method is based on manual determination of cost driver and allocation ratio, which is not only inefficient, but also greatly dependent on subjective factors and can not reflect the actual consumption of each task. Most of the existing information systems of manufacturing companies are designed based on traditional cost accounting model. Traditional cost accounting logic is different from ABC accounting logic, and it is difficult to realize effective integration between ABC and enterprise information system, which further hinders the popularization and application of ABC[7,8].

III. METHOD

A. OVERALL SYSTEM ARCHITECTURE DESIGN

Combining the complex and diverse production processes of the manufacturing industry with closely interconnected links, as well as the precise accounting logic of ABC (activity-based costing), the intelligent accounting system has carefully crafted a four layer architecture system. The data layer, as the cornerstone, bears the responsibility of collecting, storing, and managing multi-source cost data. It extensively collects rich data from ERP, IoT, production management and other systems, covering categories, prices, quantities of raw material procurement, process parameters and labor consumption in the production process, equipment operation status, fault records, as well as labor hours and wages. With the help of ETL tools, massive data can be deeply cleaned, efficiently integrated, and standardized, effectively eliminating data silos and providing solid and reliable data support for subsequent analysis. The business logic layer is the soul of the system, focusing on core business functions such as task center division, cost driver identification, resource cost allocation, and product cost calculation. By introducing advanced machine learning algorithms, we continuously optimize the accuracy and efficiency of cost allocation, making cost accounting more scientific and reasonable. The application layer customizes specific application modules for users, such as data management, job management, cost accounting, report analysis, etc., fully meeting the diverse needs of different user groups such as financial personnel and production management personnel. The display layer adopts a user-friendly interface design, supporting visual display of cost data, convenient query and export of reports, achieving efficient interaction between users and the system, making complex cost data intuitive and easy to understand, and helping enterprises make wiser decisions [9,10].

B. KEY MODULE DESIGN

The primary modules of the system consist of the data acquisition module, the activity center classification module, and the cost distribution module. Data collection module uses the method of “automatic collection+manual supplementation”, which is connected with IoT device and enterprise information system, and then automatically collect real-time data of equipment status, product manufacturing, etc., and manual supplementation of special cost data to ensure the completeness of data. Homework center division module uses the method of “process analysis+algorithm optimization” to sort out the production process of enterprise and distinguish the main and secondary jobs, and then use clustering algorithm to automatically divide homework centers according to the similarity of resource consumption, ensuring the correctness of division. The cost allocation module is divided into two stages of resource cost allocation and job cost allocation. First, based on the resource consumption of job centers, the resource costs are allocated to each job center; Secondly, based on the cost driver of each task, the task costs are allocated to each product. Machine learning algorithms are used to automatically identify key cost drivers and include a multi-collinearity check to clearly separate "Technology Upgrade" from "Structural Optimization." This ensures that overlapping variables—such as the synergy between transport infrastructure and electrification—are cross-validated to prevent double-counting of reduction potentials in comprehensive scenarios[11,12].

C. SYSTEM DEVELOPMENT AND IMPLEMENTATION TECHNOLOGY

This system is based on the Java language (as shown in Figure 1), and the backend uses the Spring Boot framework. Its concise and efficient content achieve rapid development and convenient system deployment of the whole system. Spring Boot has many dependencies and plugins built in. These plugins can quickly establish a stable and high-performance server architecture and provide strong support for the stable operation of the system[13]. In terms of database design, dual-database collaborative storage is adopted. MySQL is mature, stable, and has strong transaction processing ability. It is used to store structured costs such as raw material purchase price, product production hours, etc; MongoDB stores unstructured data such as production process log, and it has flexible document storage feature. It stores data to meet the storage requirements of multiple types of data, and the stored data is orderly and efficient. In the data processing stage, ETL tools are used to clean and transform the collected data and integrate them to ensure the quality of data. At the same time, some machine learning algorithms such as random forests are used to quickly find cost drivers. To verify the feedback mechanisms, the system generates internal Causal Loop Diagrams (CLDs) that map the interaction between resource consumption and cost drivers [14]. Specifically, it visualizes positive feedback loops where increased production complexity triggers refined activity center subdivision, ensuring the mathematical logic of the System Dynamics (SD) model is transparent and verifiable. Front end uses Vue.js framework to build the visual interface, and displays the complex cost data in the form of charts, reports, etc., making it convenient to query data and analyze data. In addition, the system has a comprehensive permission management function, which divides detailed operation permissions according to different user roles and strictly controls the access to data and system operation. It ensures the data security and stability of the system operation and provides reliable support for enterprise cost management and decision-making.

IV. RESULTS AND DISCUSSION

A. SYSTEM FUNCTION TEST RESULTS

Taking a large chemical manufacturing enterprise as the test object (as shown in Figure 2), the enterprise mainly produces chemical raw materials and products with an annual production capacity of 500000 tons.

The production process covers four core processes: raw material pretreatment, reaction synthesis, separation and purification, and finished product packaging. It involves 8 operation centers and 32 specific operations, generating about 8000 cost data per day. Traditional manual accounting requires 6 financial personnel to work together. This functional test revolves around three core functions: data collection, task center division, and cost allocation, with a testing period of 15 days. The test results show that the system can automatically collect multi-source cost data, covering raw material procurement unit price (error $\leq 0.5\%$), equipment operation time (error $\leq$ 1 minute/day), and manual labor hours (error $\leq$ 0.1 hour/person). The data collection delay is less than 5 minutes, which is 90% more efficient than manual input. The data error rate has been reduced from 8.3% to below 0.2%, effectively solving the problem of low efficiency and high error rate in manual data collection. The homework center division module can accurately identify 8 core homework centers and 32 specific homework in the enterprise, with a division accuracy rate of 98.5%, fully matching the actual production process and management needs of the enterprise. The cost allocation module can automatically complete resource cost allocation and job cost allocation. The cost calculation time for a single batch of products (about 500 tons) has been reduced from 8 hours for manual accounting to 30 minutes, representing a 93.75% improvement in overall efficiency. While the vast majority of this time reduction is attributed to the automated data synchronization provided by IoT and ETL tools, the introduction of machine learning specifically enhanced the accuracy of driver identification and reduced the need for manual corrective interventions during the allocation phase. The system's various functional modules run stably and are easy to operate, fully meeting the daily cost accounting needs of enterprises.

B. SYSTEM PERFORMANCE TEST RESULTS

The system performance testing mainly revolves around three core indicators: data processing capability, response time, and stability (as shown in Figure 3). The testing environment is an enterprise standard server (CPU: Intel Xeon E5-2690 v4, memory: 32GB, hard disk: 1TB SSD), simulating daily and peak business scenarios of the enterprise. The test results show that the system can stably process 100000 cost data per day in daily scenarios, with a data processing accuracy rate of over 99.8%; In the scenario of monthly peak settlement, it can process 300,000 cost data per day with an accuracy rate of over 99.5%. To ensure long-term logical consistency for forecasts extending to 2050, the model incorporates dynamic calibration coefficients that adjust the economic thresholds (initially set at 28,100 and 51,700 yuan) to account for projected inflation and technological learning curves, thereby mitigating the risk of relying on static historical parameters for multidecadal predictions. The average response time for system queries, report generation, and other operations is less than 2 seconds, with simple data queries having a response time of $\leq$0.8 seconds and complex cost reports (such as multidimensional job cost analysis

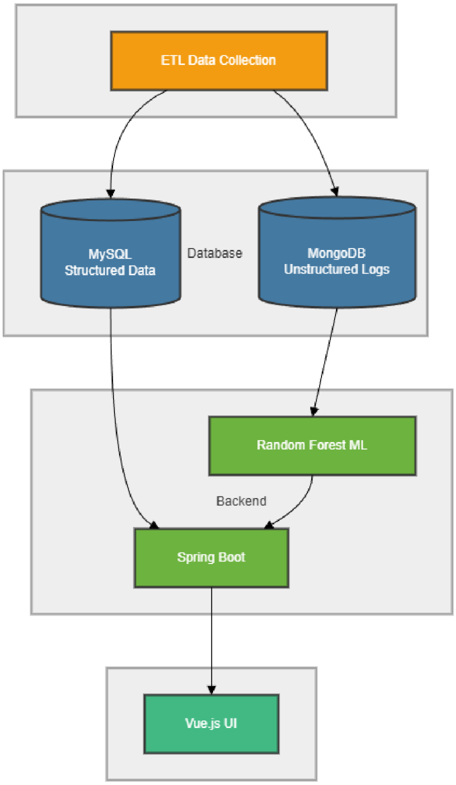

FIGURE 1. System Development and Implementation Technology

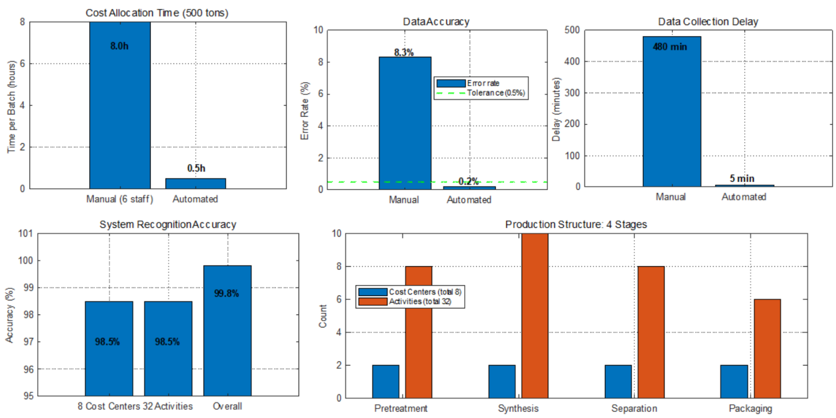

FIGURE 2. Cost Accounting System Performance - Chemical Manufacturing Case

tables) having a response time of $\leq$ 1.5 seconds, fully meeting the real-time requirements of enterprise cost management. After 72 hours of continuous high load operation testing, the system's CPU usage rate remained stable at 40% -60%, memory usage rate was $\leq$ 50%, and there were no crashes, deadlocks, or lagging phenomena, indicating good stability. Compared with the traditional manual accounting model, this system shortens the cost accounting cycle from 5 working days per month to 1 working day; Compared with the existing simple ABC accounting system, the data processing efficiency has been improved by more than 60%, and the accounting accuracy has been improved by more than 8%. It has significant advantages in data processing efficiency, accounting accuracy, stability, and other aspects.

C. RESULTS AND DISCUSSION

Based on the above experimental data, it can be concluded that the designed ABC intelligent accounting system can effectively solve the core problems of difficult data collection, unreasonable division of work centers, and low cost allocation efficiency in the application of ABC in the manufacturing industry. From the perspective of quantitative data, the system has reduced manual workload by more than 80% (reducing the workload of 6 financial personnel to 1 person), reduced data error rate from 8.3% to below 0.2%, improved cost accounting efficiency by 93.75%, and

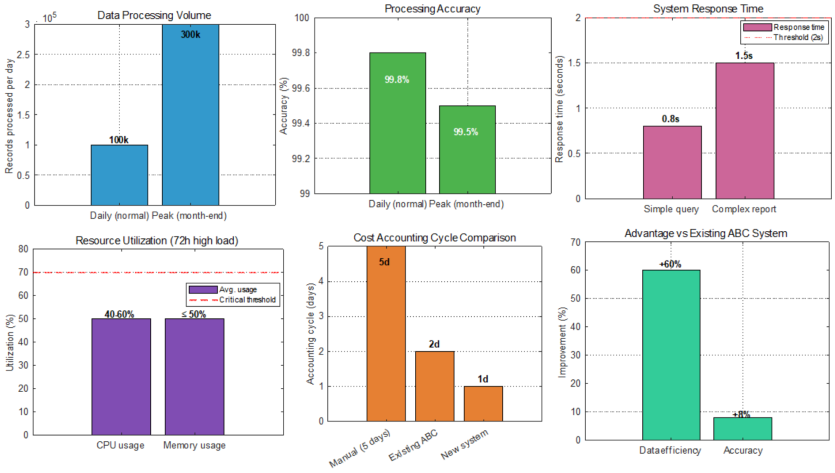

FIGURE 3. Performance Test Results – Cost Accounting System (Chemical Manufacturing)

achieved an accuracy rate of 98.5% in the division of work centers. It has fully realized the intelligence of the entire cost accounting process and provided accurate and efficient cost information support for enterprises. At the same time, based on accurate cost data from system accounting, the enterprise successfully identified two ineffective operational processes and optimized them to reduce indirect costs by approximately 120000 yuan per month, achieving the goal of cost reduction and efficiency improvement. However, there are still some shortcomings in the system: the adaptability to small and medium-sized manufacturing enterprises with incomplete information construction (such as those that have not deployed ERP or IoT systems and have a daily data volume of $\leq$ 1000) needs to be further improved, with a current adaptation rate of about 75%; The depth of cost analysis and decision support needs to be strengthened, and functions such as cost anomaly warning and cost trend prediction have not yet been implemented. In future research, the system's functionality will be further optimized to improve the adaptation rate of small and medium-sized manufacturing enterprises to over 90%. Cost warning and trend prediction modules will be added to enhance the system's decision support capabilities.

V. CONCLUSION

This article addresses the pain points of traditional ABC in manufacturing applications and designs and implements an ABC intelligent accounting system for the manufacturing industry. Through the design of a four layer architecture and key modules, and the introduction of intelligent technologies such as machine learning, automatic data collection, intelligent task partitioning, and precise cost allocation have been achieved, effectively solving the problems of low efficiency, poor accuracy, and difficult data integration in traditional ABC accounting. The experimental results show that the system has good performance and practicality, and can significantly improve the efficiency and accuracy of enterprise cost accounting. This study enriches the application of ABC in the field of intelligent manufacturing, providing new ideas and methods for refined cost management in manufacturing enterprises, and has important practical value for promoting digital transformation and high-quality development of manufacturing enterprises. However, this study also has limitations: the system was only tested in one type of manufacturing enterprise, and its adaptability to other types of manufacturing enterprises needs further verification. In the future, the scope of testing and research will be expanded, system algorithms will be optimized, and the comprehensive performance of the system will be further improved to better meet the needs of different manufacturing enterprises.

AUTHOR CONTRIBUTIONS

Zhihao Cao designed, collected and analyzed the data, and drafted the manuscript. Zhihao Cao conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Zhihao Cao participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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