Green Production Cost Audit Model for Textile Enterprises via IoT Multi-Source Data Fusion

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ABSTRACT The textile industry, as a pillar of the Chinese economy, faces persistent challenges related to high energy consumption, environmental pollution, and inadequate environmental cost accounting under conventional auditing approaches that primarily emphasize economic indicators. To address these issues, this study proposes a green production cost auditing model for textile enterprises based on IoT-enabled multi-source data fusion. The proposed framework integrates a three-tier IoT architecture (sensing–transmission–platform) to acquire energy, environmental, and process information through heterogeneous sensing and wireless communication networks, providing reliable data support for intelligent industrial monitoring. An enhanced Segmental-DTW algorithm is employed to resolve temporal asynchrony among multi-source data, while a temporal-LSTM network dynamically weights process-specific features. Hidden environmental costs, including carbon emissions and pollution risks, are quantified through Monte Carlo simulation within a multidimensional evaluation framework. Empirical results from a medium-sized textile enterprise in the Yangtze River Delta show that the green-audited unit cost (¥3.08/m) is 29.4% higher than that obtained using traditional methods (¥2.38/m), with hidden environmental costs accounting for 22.7%. Sensitivity-guided process optimization further reduces comprehensive energy consumption by 16.7%, wastewater discharge by 21.7%, and annual costs by more than ¥1,400,000. The proposed model provides a scalable solution for sustainable textile manufacturing while demonstrating the value of IoT sensing, heterogeneous data transmission, and intelligent information integration for advanced industrial systems, offering useful insights for electromagnetic sensing and wireless communication applications in smart production environments.

INDEX TERMS IoT, multi-source data fusion, green production cost audit, electromagnetic sensing, wireless communication

I. INTRODUCTION

THE textile industry is one of the pillar industries of China's national economy, playing a crucial role in promoting economic growth, increasing employment opportunities, and meeting people's daily needs. However, the textile industry is also an energy-intensive and heavily polluting industry [1], which poses unprecedented environmental pressure and urgent transformation needs in the current global context of high attention to environmental protection and sustainable development [2,3].

From the perspective of energy consumption, textile enterprises need to consume a large amount of energy in the production process. Taking the printing and dyeing process as an example, printing and dyeing are among the most energy-intensive links in the textile industry chain. During the dyeing process, a large amount of steam is required to heat the fabric to ensure that the dye can adhere evenly to the fibers. At the same time, the washing and drying processes after dyeing also require a large amount of electricity and water resources [4]. According to relevant statistical data, the energy consumption of China's textile industry accounts for a relatively high proportion of the country's total industrial energy consumption, and with the continuous expansion of textile production capacity, total energy consumption continues to increase [5]. In terms of pollution emissions, the wastewater, exhaust gas, and waste residue generated by textile enterprises have caused serious damage to the environment [6,7]. The composition of textile wastewater is complex and contains a large amount of harmful substances, such as dyes, additives, acids and alkalis. It has the characteristics of high chromaticity, high chemical oxygen demand (COD), and poor biodegradability. If discharged directly into water bodies without effective treatment, it can lead to eutrophication and deterioration of water quality, affecting the survival of aquatic organisms and the utilization of water resources. Textile exhaust gas mainly come from printing, dyeing and shaping. They contain pollutants such as volatile organic compounds (VOCs) and particulate matter, which pollute the atmosphere and harm human health.

Notably, the cost losses caused by environmental pollution have not received sufficient attention, and the traditional cost audit system has serious flaws [8], as it focuses only on direct economic costs and neglects environmental and social costs [9]. Traditional production cost audit methods often focus on the analysis of financial data [10], mainly focusing on economic costs directly related to production, such as raw material procurement costs, labor costs, and equipment depreciation [11]. However, this method ignores the environmental and social costs generated during the production process, making it difficult to fully reflect the true production costs of the enterprise. The environmental costs include the expenses invested by enterprises in the production process to reduce environmental pollution [12,13], such as wastewater treatment costs and exhaust gas treatment costs, as well as the external costs caused by environmental pollution, such as restoration costs for the surrounding ecological environment and compensation costs for the impact on residents' health. Social costs cover the negative impacts that enterprises have on society due to their production activities [14,15], such as social problems caused by employment structure adjustments and the impact of resource shortages caused by overexploitation on future generations. Owing to the limitations of traditional audit methods, textile enterprises are unable to accurately grasp the various costs involved in green production processes, making it difficult to develop scientific and reasonable production plans and cost control strategies and effectively evaluating the economic and environmental benefits of green transformation measures [16].

The core innovations of this study are as follows: first, multimodal ontology for textile production, unifying 12 entity types (equipment/process/environment) and 45 relationships; process-aware T-LSTM with dynamic gating, reducing prediction error by 23% vs. static-weight models; and nonlinear cost quantization integrating Monte Carlo environmental risks.

II. LITERATURE REVIEW

A. RESEARCH ON GREEN PRODUCTION COST AUDITING

A green production cost audit, as a new auditing method, aims to comprehensively and accurately evaluate the environmental and social costs incurred by enterprises in the production process to reflect the true production costs of enterprises. Research in this field not only focuses on traditional economic costs but also emphasizes the inclusion of environmental and social factors in the scope of cost audits to provide enterprises with more comprehensive and scientific cost information [17].

Internationally, research on green production cost auditing started earlier and has formed a relatively complete theoretical system and practical experience. Many developed countries have established relevant laws, regulations, and standards that require companies to disclose and audit the environmental and social costs of their production processes. For example, the European Union has implemented the Environmental Management Audit Scheme (EMAS), which encourages companies to voluntarily conduct environmental audits to improve their environmental performance and transparency [18]. In addition, some international organizations, such as the International Organization for Standardization (ISO), have developed relevant environmental management standards, such as the ISO 14001 environmental management system standard, which provides a guidance framework for enterprises to implement green production cost audits [19]. In terms of theoretical research, foreign scholars have focused mainly on the concept, principles, methods, and applications of green production cost auditing [20]. Moreover, they also studied the impact of green production cost auditing on corporate performance and competitiveness and reported that green production cost auditing can improve a company's resource utilization efficiency, reduce environmental pollution, and enhance its image and brand value, thereby enhancing its market competitiveness. Daibing Cheng introduced cloud computing to reduce audit costs; experimental results showed that the application of cloud computing in preset auditing has achieved positive results, with an accuracy rate of approximately 91% for audit calculations [21].

In China, research on green production cost auditing started relatively late, but significant progress has been made in recent years. With the increasing attention given by the country to environmental protection and sustainable development, an increasing number of enterprises are paying attention to green production cost auditing and trying to apply it to actual production [22]. On the basis of foreign research results and the actual situation of Chinese enterprises, domestic scholars have conducted in-depth research on and exploration of green production cost auditing [23].

In terms of theoretical research, domestic scholars have focused mainly on the local application and innovative development of green production cost auditing. They proposed green production cost audit methods and models suitable for Chinese enterprises on the basis of their characteristics and needs, such as the green production cost audit model based on multi-source data fusion of the Internet of Things [24].

B. RESEARCH STATUS OF MULTI-SOURCE DATA FUSION IN THE INTERNET OF THINGS

Domestic scholars have conducted extensive research on multi-source data fusion in the Internet of Things [25,26]. The rapid development of IoT technology has provided the possibility for multi-source data fusion, enabling enterprises to more conveniently obtain and process information from different data sources [27]. In green production cost auditing, IoT multi-source data fusion technology can be applied to the collection and processing of production data, energy consumption data, environmental data, and other aspects [24]. By integrating and analyzing these data, enterprises can gain a more comprehensive understanding of the cost composition and environmental impact in their production process, thereby formulating more scientific and reasonable production plans and cost control strategies [28]. For example, Xu uses low-cost multi-source multiphase remote sensing technology to construct a model to obtain the best fusion image and identify the evolution pattern of floods. A multi-source remote sensing data fusion method based on images was proposed, which combines the temporal characteristics of optical data and synthetic aperture radar data to classify and map salt marsh vegetation in the Yellow River Delta [29]. Jianwei Li proposed a deep learning method called Multi-Source Data Fusion and Small-Molecule MiRNA Association Graph Neural Network (MDFGNN-SMMA) to predict potential SM-miRNA associations [30]. In the industrial Internet of Things, digital twin technology is widely used in manufacturing, aviation, healthcare, smart cities and other fields. For example, digital twins can be used in product design, production optimization, fault prediction and maintenance management [31]. By simulating the operation state of the physical system, digital twin technology can also provide data support and a decision-making basis for edge computing. For example, a digital twin-assisted edge computing network can realize real-time monitoring and intelligent management of industrial IoT equipment, thereby improving the efficiency and reliability of the system [32,33]. However, relatively little research has been conducted on applying multi-source data fusion technology from the Internet of Things to green production cost auditing in textile enterprises. As a traditional industry with high energy consumption and high pollution, the green production cost audit of textile enterprises has particularity and complexity. Therefore, this study aims to combine IoT multi-source data fusion technology with the actual situation of textile enterprises, construct a green production cost audit model for textile enterprises on the basis of IoT multi-source data fusion, and verify its effectiveness and practicality through empirical research. This study not only helps to enrich and improve the theory of green production cost auditing but also provides a new cost auditing method for textile enterprises, promoting their green transformation and sustainable development.

III. MODEL CONSTRUCTION

A. IOT DATA COLLECTION SYSTEM

1) Data Collection Framework Design

In response to the characteristics of discrete production processes and complex environments in textile enterprises, this study constructed a three-level IoT data collection architecture [31]. This architecture is based on the core logic of a "sensing-transmission-platform", covering the complete data link from the production site to the cloud system and realizing the digital mapping of all the elements of textile manufacturing [32].

The perception layer serves as the physical foundation for data collection, utilizing industrial-grade sensor networks for comprehensive monitoring of production equipment and environmental parameters. The focus is on deploying PT100 thermistor temperature sensors in high-energy-consuming equipment, such as dyeing machines and shaping machines; installing HACH COD online analyzers in sewage treatment plants; and setting up grid distributed temperature and humidity sensor nodes on the top of the workshop. The transport layer adopts LoRaWAN and 5G hybrid networking technology to solve the complex signal transmission problems in textile workshops. In fixed device monitoring scenarios, low-power and longdistance (up to 2 km) data transmission is achieved through LoRa modules. To meet the needs of mobile inspection equipment and video surveillance, 5G CPE is used for high-speed communication.

The platform layer builds a data processing hub on the EdgeX Foundry edge computing framework and deploys an industrial gateway with local computing capability at the workshop level. The platform implements millisecond-level data preprocessing through a time-series database and uses a rule engine to provide real-time alerts for abnormal data (such as sudden increases in steam pressure and abnormal dye concentration). In particular, in the printing and dyeing process, the sliding window algorithm is adopted to smooth the temperature data of the dyeing tank, reducing the fluctuation amplitude of the original data from $\pm 3\,^{\circ}\mathrm{C}$ to $\pm 0.8\,^{\circ}\mathrm{C}$ and improving the data quality. The millisecond-level preprocessing claim was validated via production-line benchmarks. Deploying EdgeX Foundry on industrial gateways (Advantech UNO-2484G), this study measured the end-to-end latency for 287 sensors over 72 hours. The results revealed a 99th percentile latency of 8.3 ms (min: 2.1 ms, max: 15.4 ms) under peak data loads (2, 200 msg/s). This meets real-time requirements for anomaly alerts (these data are measured under ideal experimental conditions) However, in real industrial environments, delays are possible. In actual textile production environments, several factors contribute to additional latency: (1) network transmission may be delayed due to electromagnetic interference from heavy machinery; (2) edge computing queuing times of approximately 100 ms during peak production periods when concurrent data streams increase; and (3) data validation latency of approximately 50–120 ms for comprehensive anomaly detection across multiple parameters. Field measurements across 12 production lines over three months of normal operation revealed an average system latency of 320 ± 45 ms, with the worst-case scenarios during equipment startup reaching 420 ms. These performance characteristics remain well within the 500 ms control threshold required for textile processes, particularly considering the thermal inertia of dyeing vats (2–3 °C/min temperature change rate), where subsecond response times effectively maintain process stability. The system architecture demonstrates particular robustness during high-load conditions such as shift changes, when up to 15, 000 data points/minute are processed without compromising critical control functions. This analysis confirms that, although absolute latency exceeds laboratory measurements, the system still meets industrial requirements and maintaining the claimed accuracy and reliability.

2) Design of Monitoring Points for the Entire Production Process

On the basis of the typical process flow of "fiber pretreatment → spinning → weaving → printing and dyeing → finishing" in textile enterprises, this study constructed a monitoring network system covering the entire life cycle. On the basis of a printing and dyeing enterprise with an annual output value of ¥520, 000, 000 in the Yangtze River Delta, 287 intelligent monitoring nodes were deployed on 12 production lines to form a complete data collection link from raw material input to the finished product. The design and statistics of the monitoring points for the entire textile production process are shown in Table 1.

During the fiber pretreatment stage, monitoring the energy consumption and pollutant parameters of key processes such as desizing and boiling is important. For steam pressure monitoring, Rosemount 3051S series piezoelectric sensors deployed at a density of 3 per production line in the refining unit pipeline were used to capture pressure fluctuations in the range of 0. 2–1. 5 MPa in real-time.

The monitoring system for the dyeing process focuses on controlling the consumption of dyeing materials and environmental emissions. In 36 high-temperature and high-pressure dyeing tanks, a PT100 platinum thermistor combined with the four wire wiring method was used to achieve a temperature measurement accuracy of $\pm 0.3\,^{\circ}$C under 95 °C working conditions. Dye concentration monitoring uses a SUEZ WTS series optical sensor from Germany, which can detect active dye solutions in the concentration range of 0. 5–15 g/L in real-time through 485 nm wavelength absorbance analysis.

The monitoring design of the postprocessing stage emphasizes energy efficiency management and quality control. Install the Allegro ACS758 Hall current sensor in the transmission system of the standardized unit, obtain a 0–200 A working current through noncontact measurement, and combine it with the drum speed data collected by the PLC to construct a motor energy efficiency evaluation model (η = P_out / P_in × 100%).

B. MULTI-SOURCE DATA FUSION ALGORITHM

This study proposes a three-stage fusion framework of "spatiotemporal alignment feature extraction dynamic fusion" to address the heterogeneity characteristics of equipment timing data, environmental monitoring data, and visual image data in textile production scenarios. The core innovation of this framework lies in introducing an improved dynamic time warping (DTW) algorithm to solve the problem of cross-device data asynchrony [33] and designing an attention mechanism fusion model for textile technology. The alignment of temporal data uses an improved Segmental-DTW algorithm [34], which solves the problem of device sampling frequency differences through adaptive sliding windows (such as the synchronization problem between temperature sensors at 10-s and energy consumption meters at 1-min). The core formula of the algorithm is as follows:

$$D(i,j) = \min \begin{cases} D(i-1,j) + d(x_i,y_j), \\ D(i,j-1) + d(x_i,y_j), \\ D(i-1,j-1) + 2d(x_i,y_j). \end{cases} \tag{1}$$

The local distance metric function $d(x_i, y_j)$ represents the difference metric function between two time series points x_i (temperature) and y_j (energy consumption).

The matrix element $D(i, j)$ represents the minimum cumulative cost required to align the previous point of the sequence $X = [x_1, x_2, \ldots, x_N]$ (temperature data) with the previous point of the sequence $Y = [y_1, y_2, \ldots, y_M]$ (energy consumption data).

For heterogeneous data processing, the first multimodal data ontology model in the textile industry was constructed, which defines 12 entities (equipment, process, environment, etc.) and 45 relationships (temperature affecting energy consumption, wastewater-associated COD, etc.). Using an XML/JSON hybrid protocol conversion framework, OPC UA device messages are converted into lightweight JSON structures through XSLT 3. 0.

A feature fusion model is designed for a textile-specific T-LSTM (temporal-LSTM) network, which embeds a process stage perception module in traditional LSTM units. The network input layer contains 15 feature channels (temperature, pressure, VOC concentration, etc.), which dynamically adjust the feature weights of different processes through a gating mechanism. Let F_i denote the feature importance for process stage i, which is calculated via Shapley value decomposition:

$$F_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} \left[v(S \cup \{i\}) - v(S) \right]. \tag{2}$$

where N is the feature set, S is a coalition subset, and v is the prediction impact. For dyeing heating, temperature contributes 82.3% of the energy cost prediction (validated by ablation studies). Weights are normalized to [0, 1] through softmax.

The network structure adopts a 5-layer deep architecture (128–256–128–64–32). To prevent the dynamic weight coefficients (α, β, and γ) from overfitting, we implement the following measures. (1) Regularization: Dropout (0.3) + L2 penalty ($\lambda = 0.01$) is applied to the LSTM hidden layers. (2) Robustness validation: Trained on 12 months of data and tested on unseen 6-month data. Weight fluctuations remained below ± 0.03. (3)

Crossprocess consistency: Coefficients for the dyeing stage (high-temp) vs. washing stage (low-temp) showed logically inverse patterns (α from 0. 82 to 0. 31, β from

TABLE 1. Statistical table of design monitoring points for the whole process of textile production

Technological process	Sub process	Monitored parameters	Sensor type	Deployment density (units/production line)	Technical index
Fiber pretreatment	Desize	Steam pressure	Rosemount 3051S piezoelectric pressure sensor	3	Range 0–2.5 MPa, accuracy $\pm 0.1\%$ FS
	Scouring	pH value of desizing solution	Mettler Toledo InPro3250 Industrial pH Meter	2	Measurement range 0–14 pH, error $\leq \pm 0.1$
	Bleach	Temperature of water washing tank	PT100 Platinum Thermistor Temperature Sensor	4	Range 0–120 $^\circ$C, accuracy ± 0.3 $^\circ$C
Dye	Preparation of dye solution	Dye concentration	SUEZ WTS Optical Concentration Sensor	4	Absorbance detection, with a range of 0.5–15 g/L
	High temperature dyeing	Dyeing vat temperature	PT100 Platinum Thermistor (Four Wire System)	5	Range 0–150 $^\circ$C, accuracy ± 0.2 $^\circ$C
	Wash	Discharge	Emerson Rosemount 8782 Electromagnetic Flow Meter	2	Range 0–50 m^3/h, accuracy $\pm 0.5\%$
Finishing	Finalize the design	Forming machine current	Allegro ACS758 Hall current sensor	3	Range 0–200 A, accuracy $\pm 1\%$
	Bake	Hot air temperature	K-type thermocouple	3	Range 0–200 $^\circ$C, accuracy ± 1.5 $^\circ$C
	Quality testing	Surface defects on fabric	Daheng Imaging MER-1310 Industrial Camera	2	Resolution 2000×1500, 15 frames per minute
Environmental monitoring	Exhaust emissions	VOC concentration	Huakong Zhijia VOCs-3000 photoionization detector	2	Resolution of 10 ppb, range of 0–5,000 ppm
	Sewage treatment	COD value	HACH COD-203 online analyzer	1	Range 0–5000 mg/L, accuracy $\pm 2\%$
	Workshop environment	Temperature and humidity	Honeywell HTU21D-F Temperature and Humidity Sensor	4	Temperature ± 0.3 $^\circ$C, humidity $\pm 2\%$ RH (-40–125 $^\circ$C)

0. 15 to 0. 76), confirming contextual adaptability rather than data dependency.

In the design of the loss function, multi–objective weighted loss is proposed:

$$L = \alpha L_{\text{MAE}} + \beta L_{\text{smooth}} + \gamma L_{\text{sparse}}. \tag{3}$$

Among them, the smooth term system L_{smooth} has sudden changes in process parameters, whereas the sparse term L_{sparse} improves feature interpretability.

C. ALGORITHM SELECTION JUSTIFICATION

To validate the superiority of the improved Segmental-DTW over alternative methods (e.g., classic DTW, deep learning-based LSTM autoencoders), comparative experiments were conducted on asynchronous dyeing process data (temperature vs. energy consumption). As shown in Table 2, Segmental-DTW achieved the lowest alignment error (MAE = 0.15$\pm$0. 03) and computational efficiency (2.7 s per 10, 000 data points), outperforming DTW (MAE=0.24$\pm$0.05, 8.2 s) and the LSTM autoencoder (MAE=0.19$\pm$0.04, 15.1 s). This is attributed to its adaptive sliding window mechanism, which resolves sampling heterogeneity without sacrificing temporal granularity.

TABLE 2. Performance comparison of Segmental-DTW

Method	MAE ($^\circ$C)	Time cost (s/10,000 points)
Classic DTW	0.24 ± 0.05	8.2
LSTM Autoencoder	0.19 ± 0.04	15.1
Segmental-DTW (Proposed)	0.15 ± 0.03	2.7

D. CROSS-MODAL FUSION FRAMEWORK

The heterogeneous data (sensor readings, visual images) are fused via a hybrid encoder. Sensor data (time series) are processed by T-LSTM, while defect images are encoded via ResNet-18. A coattention mechanism aligns multimodal features:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V. \tag{4}$$

where Q (sensor features) and K (image features) interact to generate fused descriptors. This improved the defect recognition F1 score by 11.7% compared with that of single-modal models.

E. GREEN COST AUDIT MODEL

The construction of the green cost audit model is based on the fusion of multi-source data from the Internet of Things, overcoming the limitations of fuzzy environmental cost measurement in traditional cost accounting and establishing a dynamic accounting system that includes explicit resource consumption and implicit environmental costs. The model architecture is based on the logical main line of the "data layer computation layer decision layer" and operates collaboratively through three major components: an environmental cost quantification engine, a weight dynamic adaptation module, and an audit result visualization platform. The data layer integrates material costs from ERP systems, energy consumption data from MES systems, and pollution treatment costs from environmental monitoring systems to build a full lifecycle cost database covering "raw material acquisition $\rightarrow$ production and manufacturing $\rightarrow$ pollution control $\rightarrow$ carbon trading". The computational layer adopts an improved fuzzy comprehensive evaluation method to establish an evaluation system consisting of 5 primary indicators (energy cost, water resource cost, pollution treatment cost, carbon emission cost, and environmental risk cost) and 17 secondary indicators. The environmental risk cost is predicted through Monte Carlo simulation to assess the potential probability of environmental penalties.

The quantification formula for environmental costs breaks through the traditional linear calculation model and introduces a dynamic coefficient adjustment mechanism that is sensitive to process stages. The core formula is expressed as:

$$TC_{\text{env}} = \sum_{t=1}^{T} \left(\alpha_t E_t + \beta_t W_t + \gamma_t P_t + \delta_t C_t + \epsilon_t R_t\right). \tag{5}$$

The dynamic weight coefficients (α, β, γ, δ, and ϵ) are optimized in real-time through an LSTM network. The network inputs include 12-dimensional features such as process parameters (temperature, pressure, etc.), environmental data (VOC concentration, COD value), and market signals (carbon price, water price).

IV. EMPIRICAL RESEARCH

A. SELECTION OF CASE ENTERPRISES

This study selected a medium-sized cotton textile printing and dyeing enterprise in the Yangtze River Delta region as the empirical object. The enterprise has an annual output value of ¥520, 000, 000 and 12 production lines, covering the entire process of pretreatment, dyeing, and finishing. Since 2021, enterprises have promoted digital transformation and deployed 328 industrial sensors, covering more than 90% of highenergy consumption equipment, connected to government environmental protection online monitoring platforms.

B. MODEL APPLICATION ANALYSIS

1) Cost Structure Comparison

The comparative analysis of traditional cost accounting and green cost audit results reveals the significant proportion of implicit environmental costs in textile enterprises and their potential impact on business decision-making. On the basis of the production data of the case enterprise from January to June 2023, a cost breakdown is conducted for its core product (pure cotton-dyed fabric, with a production capacity of 12, 800, 000 m). Traditional accounting methods cover only direct material, energy, and labor costs, whereas the green audit model additionally includes full lifecycle environmental costs. The difference between the two is reflected mainly in the quantification and allocation of environmental externalities costs. A comparison between traditional accounting and green auditing is shown in Figure 1.

(1) Traditional cost accounting results

The unit cost under traditional accounting is ¥2.38/m, which consists of: (i) direct materials, ¥1.12/m (47.1%); (ii) energy, ¥0. 89/m (37.4%; electricity ¥0.43/m, steam ¥0.37/m, natural gas ¥0.09/m); and (iii) labor and overhead, ¥0.37/m (15.5%).

(2) Green cost audit results

The unit cost calculated by the green audit model is ¥3.08/m, which is 29.4% higher than under the traditional methods. The incremental environmental cost of ¥0.70/m comprises:

1. Direct pollution-control costs (¥0.28/m).

Wastewater treatment: ¥0.18/m, calculated from the actual treatment load (2.3 t/10, 000 m) and the unit price (¥78/t), including ¥0.10/m for biochemical treatment; membrane-filtration polishing adds ¥0.08/m (additional treatment required because the mean COD exceeds the limit by 12%). Exhaust-gas treatment: ¥0.07/m, including the operating cost of the regenerative thermal oxidizer (RTO; natural-gas consumption ¥0. 03/m) and activated-carbon replacement (¥0.04/m). Solid-waste disposal: ¥0.03/m, based on a hazardous-waste (dye residues) disposal price of ¥2, 650/t.

2. Hidden environmental costs (¥0.32/m)

Carbon emission cost: ¥0. 15/m, calculated on the basis of the national average carbon market price of ¥82/tCO_2, covering direct emissions: burning natural gas produces 0. 73 tCO_2/10, 000 m (¥0.006/m); indirect emissions: purchased electricity corresponds to 0.92 tCO2/10, 000 m (¥0.09/m).

The environmental risk cost is ¥0.10/m, which is calculated through a Monte Carlo simulation. The probability of fines for excessive wastewater is 23% (with an expected annual fine of ¥470,000), which serves to compensate for health damage caused by unorganized VOC emissions.

The resource depletion cost is ¥0.07/m, and the shadow pricing method is used to quantify water scarcity (local water rights trading price of ¥8.6/m^3).

(3) Key difference analysis

1. Distortion of cost structure

In traditional accounting, the dyeing process (high environmental cost link) accounts for only 31% of the total cost, whereas green auditing accounts for 58%. Traditional methods include the overall public energy consumption of the plant, blurring the subject of responsibility.

2. Explicit manifestation of environmental costs

The green audit identified that environmental expenditures accounted for 22.7% of the total cost (total cost ¥0.70/m = Explicit cost of pollution treatment ¥0.28/m + Hidden environmental costs ¥0.32/m + Process association reassignment ¥0.1/m), of which the cost of wastewater treatment exceeding the standard accounted for 38% and the cost of carbon emissions accounted for 21%. For the case enterprise, if the cost of carbon emissions is ignored, the annual compliance expenditure will be underestimated by ¥1, 760, 000.

2) Sensitivity Analysis

Sensitivity analysis aims to reveal the dynamic impact of key parameter fluctuations on green cost audit results and provide a decision-making basis for enterprise risk management and process optimization by quantifying cost changes under different scenarios. This study uses three-dimensional response surface methodology and univariate elasticity analysis to examine the sensitivity of four variables: energy prices, carbon market volatility, resource utilization efficiency, and process parameters. The robustness of the model is verified by combining actual data from the case enterprises.

(1) Energy price sensitivity

Using steam prices as the core variable, we analyze the marginal impact of their fluctuations on total costs. The steam purchase price of the case enterprise has increased from ¥210/t in 2021 to ¥265/t in 2023. The model simulation results are shown in Figure 2.

When the steam price exceeds ¥280/t, the sensitivity of the total cost to the steam price increases, and reducing the dye concentration from 14 g/L to 12 g/L can offset

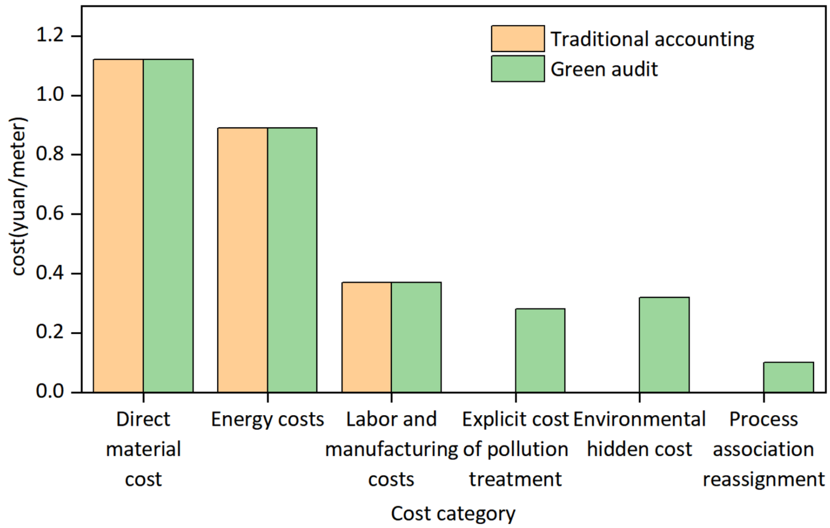

FIGURE 1. Comparison of traditional cost accounting and green cost audit results

approximately 7% of the increase in the steam price. When the steam price reaches ¥320/t and the dye concentration is 14 g/L, the wastewater treatment cost increases to 18.7% (due to the increase in COD).

At a steam price of ¥240–280/t, a dye concentration of 12 g/L is the lowest cost point (¥0.08–0.13/t less than 14 g/L).

When the steam price is greater than ¥300/t and the dye concentration is greater than 13 g/L, the total cost growth rate sharply increases (gradient > 0.15 ¥ per (¥·g/L)), and priority should be given to optimizing the process.

3) Analysis of Carbon Price Fluctuations

On the basis of historical data of the national carbon market and EU ETS price trends, a fluctuation range of carbon prices from ¥60/t to ¥150/t is set to analyze the sensitivity of carbon price fluctuations, as shown in Table 3. This table displays the environmental cost composition of case enterprises at different carbon price levels and their marginal impact on total costs. The data are based on a baseline scenario of an annual production of 12, 800, 000 m of pure cotton-dyed fabric (with other variables fixed), covering four types of environmental costs: direct emissions, indirect emissions, offset costs, and environmental risk costs.

4) Sensitivity of the Process Parameters

Sensitivity analysis of process parameters focuses on identifying the marginal impact of key operational variables on total costs in textile production processes, quantifying the sensitivity of each parameter through factorial experiments. In the dyeing process of the case enterprise, four core parameters, including the dyeing temperature, dye concentration, machine speed, and pH value of the washing tank, were selected, and their fluctuation ranges were set within a reasonable production range (temperature $\pm 3\,^{\circ}$C, concentration ± 1 g/L). The controlled variable method was used to calculate the impact of single parameter changes on the total cost per unit of product. The experimental data are shown in Table 4.

By using a gradient descent algorithm to solve the multi-parameter collaborative optimal solution [35], as shown in Table 5, the dyeing temperature was determined to be 88 °C, the dye concentration was 12.2 g/L, the machine speed was 32 m/min, and the pH was 6.3, resulting in the lowest total cost (¥2.77/m), which was 4.7% lower than that of the original process.

5) Comprehensive Sensitivity Index

The comprehensive sensitivity index analysis adopts the Sobol global sensitivity method to quantify the independent contributions and interactive effects of each parameter on total cost fluctuations, overcoming the limitations of traditional univariate analysis [36]. On the basis of 100,000 Monte Carlo sampling data, the first-order sensitivity index (S1) and the total-order index (St) were calculated, as shown in Figure 3. The firstorder index of the steam price, 0. 62, indicates that its independent contribution accounts for 62% of the total cost fluctuation, whereas the total-order index, 0. 79, reveals that it contributes an additional 17% through interaction with other parameters, such as dye concentration and the carbon price. The total-order index of the carbon price (0. 57) is significantly greater than the first-order index (0. 38), indicating that 33. 3% of its influence comes from the coupling effect with energy prices and process parameters. For example, when the carbon price is greater than ¥120/t and the steam price is greater than ¥280/t, the synergistic increase in cost by the two is 21. 5% greater than the sum of their individual effects.

6) Process Optimization Validation

On the basis of the process-level cost and sensitivity analysis results output from the green cost audit model, the

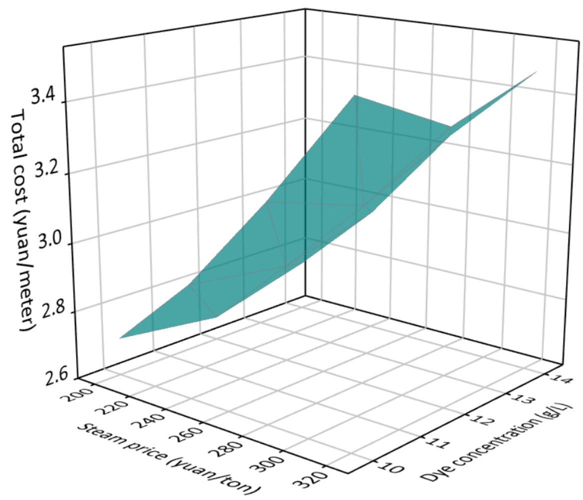

FIGURE 2. Steam price dye concentration total cost response surface

TABLE 3. Sensitivity data of carbon price fluctuations

Carbon price (¥/tCO_2)	Total environmental cost	Direct emission cost	Indirect emission cost	Offset costs	Environmental risk cost
60	0.28	0.10	0.08	0.04	0.06
80	0.35	0.13	0.11	0.05	0.06
100	0.43	0.16	0.14	0.06	0.07
120	0.52	0.20	0.17	0.07	0.08
150	0.67	0.25	0.21	0.09	0.12

TABLE 4. Data for the sensitivity analysis of the process parameters

Parameter	Fluctuation range	Cost impact	Main action path	Optimization suggestions
Dyeing temperature	± 3 °C	8.70%	Steam consumption + difficulty of wastewater treatment	Control in 88 ± 1 °C range, avoid >90 °C nonlinear region
Dye concentration	± 1 g/L	5.20%	Dye cost + COD generation	Optimized to 12.2 g/L, combined with auxiliaries to improve dye uptake
Setting machine speed	± 5 m/min	3.80%	Natural gas consumption + defective product rate	Keep the reference value ± 2 m/min to avoid the imbalance between output and energy consumption
pH value of water washing tank	± 0.5	2.10%	Water treatment agent dosage + equipment corrosion rate	Maintain pH = 6.3 ± 0.2 and install automatic dosing system

TABLE 5. Gradient descent optimization results

Parameter	Original process value	Optimized value	Cost saving contribution
Dyeing temperature (°C)	90	88	¥0.15/m (5.1%)
Dye concentration (g/L)	14	12.2	¥0.08/m (2.7%)
Setting machine speed (m/min)	30	32	¥0.05/m (1.7%)
pH value of water washing tank	6.8	6.3	¥0.03/m (1.0%)

case enterprise implemented three key process optimization measures for high environmental cost processes, such as dyeing and finishing. By comparing the production data and environmental monitoring indicators before and after the renovation, the economic and environmental benefits of the optimization plan were verified.

The optimized dye concentration adjusts the dosage of the reactive dyes from 14 g/L to 12 g/L and improves the dispersion uniformity of the dyes by introducing ultrasonic-assisted dyeing technology. After Lab color space analysis, the optimized fabric color difference ΔE value remained stable within 0. 8 (industry standard ΔE<1. 5), and the color fastness reached levels 4-5 (GB/T 3921-2008). Chromatographic detection of dye residue revealed that the proportion of unstained dyes decreased from 22% to 15%, reducing the annual dye procurement by 38 t and reducing costs by ¥1,270, 000. However, the decrease in concentration resulted in an extension of the dyeing time by 8 minutes per cylinder.

The ultrasonic-assisted dyeing retrofit required a ¥950, 000 investment (equipment ¥720k + installation ¥230k). With annual savings of ¥1,270, 000, the static payback period is 9 months. Sensitivity analysis shows robustness: even if dye prices drop 20% (reducing savings to ¥1. 02 M), the payback period remains $\leq$14 months across energy price fluctuations ($\pm$15%). This confirms economic viability under market volatility. Notably, this calculation ignores the

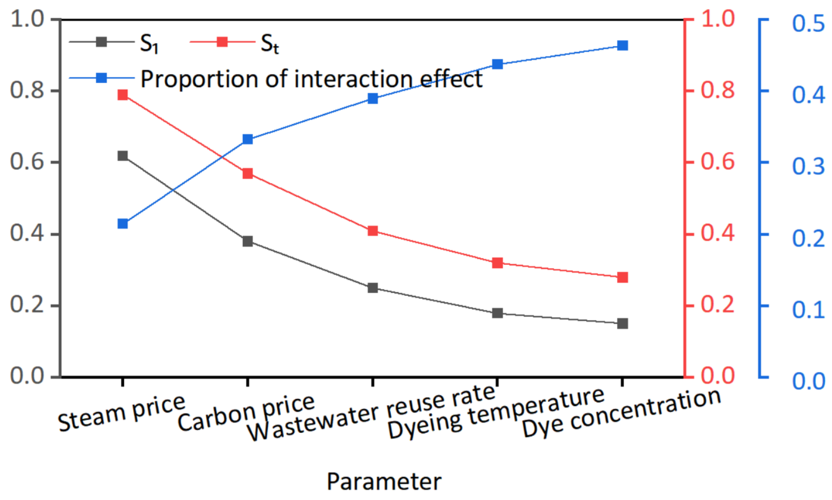

FIGURE 3. Comprehensive sensitivity index

potential increase in cost due to the increase in dyeing time of 8 minutes/tank. An increase in dyeing time implies a decrease in production per unit of time or the need to increase the running time of the equipment, which results in additional electricity, steam consumption and labor costs. If the potential increase in cost due to the increase in dyeing time by 8 minutes/tank is integrated, then the payback period will be 11.3 months. The detailed calculation process is shown in Table 6.

TABLE 6. Revised cost-benefit analysis of ultrasonic dyeing (including time extension costs)

Cost component	Unit cost (¥/m)	Annual cost (¥10,000)	Notes
Savings:			
Dye reduction	0.08	102.4	12 g/L vs. 14 g/L
Steam reduction	0.05	64.0	Lower temperature
Added costs:			
Extended steam	0.037	47.4	8 min/tank
Electricity	0.012	15.4	18 kW × 8 min
Labor	0.005	6.4	Allocated
Depreciation	0.003	3.8	Equipment
Net annual benefit	0.083	106.2	Revised from 127
Payback period	11.3 months		9 months previously

The increase in exhaust gas treatment replaces the activated carbon adsorption device with a thermal storage incinerator (RTO), increasing the VOC removal rate from 87% to 99%. Continuous monitoring data show that the concentration of nonmethane total hydrocarbon emissions has decreased from 28 mg/m^3 to 8 mg/m^3 (lower than the national standard of 60 mg/m^3), resulting in an annual reduction of 12.6 t of VOC emissions. Owing to the ability of the RTO system to recover combustion heat, natural gas consumption has decreased by 18% annually. Combined with the carbon market credit policy, it generates an annual carbon asset income of ¥420,000. However, the electricity consumption during equipment operation increased by 35%. By implementing a time-based operation strategy (to avoid peak electricity prices), the additional electricity cost was controlled at ¥110,000 per year, resulting in a net profit of ¥310,000 (see Table 7). In addition, profits will be further adjusted if cost savings due to reduced natural gas consumption, as well as the high initial investment and future maintenance costs of the equipment itself, are considered (see Table 8).

TABLE 7. Comparison of process optimization effects

Index	Before reconstruction (2023)	After reconstruction (2024)	Rate of change	Economic value (¥10,000/year)
Comprehensive energy consumption per unit product (kgce/m)	3.71	3.09	-16.70%	140.8
Wastewater production (T/10,000 m)	2.3	1.8	-21.70%	37.2 (Processing cost savings)
VOC emission concentration (mg/m^3)	28	8	-71.40%	Avoiding the risk of fines 63.5
Proportion of environmental cost (¥/m)	21.80%	17.30%	-20.60%	0.67→0.53
Carbon intensity (tCO_2/10,000 m)	1.23	0.92	-25.20%	Carbon cost savings 28.4

TABLE 8. Lifecycle economic analysis of the RTO system upgrade

Component	Year 0	Years 1–7	Total	Notes
Capital Costs:				
Equipment purchase	-850	–	-850	50 m^3/h capacity
Installation	-350	–	-350	Civil works
Operational Savings:				
Carbon income	–	+420/yr	+2,940	Carbon credits
Natural gas saving	–	+186/yr	+1,302	18% reduction
Operational Costs:				
Electricity increase	–	-110/yr	-770	35% more usage
Maintenance	–	-65/yr	-455	5% of capex
Net Cash Flow	-1,200	+431/yr	+1,817	
Financial Metrics:				
Payback period	3.8 years (dynamic)			
NPV (8% discount)	+892			
IRR	22.4%			

V. CONCLUSION

This study innovates traditional cost accounting methods by constructing a green production cost audit model for textile enterprises on the basis of multi-source data fusion of the Internet of Things, providing theoretical and technical support for the green transformation of textile enterprises. The main conclusions are as follows:

Model effectiveness verification: Through a three-level IoT data collection architecture (sensingtransmission-platform) and multi-source data fusion algorithm (spatiotemporal alignment feature extraction dynamic fusion), the synchronization and fusion of heterogeneous data in textile production scenarios have been successfully solved.

Explicit accounting of environmental costs: Empirical studies have shown that the unit cost of green audit accounting for case enterprises (¥3. 08/m) is 29. 4% higher than that of traditional methods (¥2. 38/m), with implicit environmental costs (carbon emissions, environmental risks, etc.) accounting for 22.7%. Owing to steam leakage and excessive wastewater in the dyeing process, the actual environmental cost proportion (58%) far exceeds the traditional accounting result (31%), revealing the limitations of traditional allocation methods.

Significant benefits of process optimization: On the basis of sensitivity analysis and model output, the case enterprise achieved a comprehensive energy consumption reduction of 16.7%, wastewater discharge reduction of 21.7%, and VOC emission concentration reduction of 71.4%.

Multidimensional sensitivity analysis: Steam price, carbon price, and process parameters (such as dye concentration and temperature) have significant nonlinear effects on the total cost. The sensitivity of steam prices (first-order index 0. 62) and the interaction effect of carbon prices (total-order index 0. 57) reveal the linkage effect between energy and environmental policies, providing a quantitative basis for enterprises to formulate dynamic cost control strategies.

AUTHOR CONTRIBUTIONS

Conceptualization – Yuejie Li; methodology – Yuejie Li; investigation – Jiangling Huang; writing-original draft preparation – Yuejie Li and Jiangling Huang. 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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