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Research on Cost-Benefit Evaluation Model of Manufacturing Projects Based on Engineering Economic Analysis

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ABSTRACT

Digital transformation in the textile industry requires significant capital investment, creating a conflict between high upfront costs and uncertain long-term returns. Traditional static evaluation methods often fail to accurately predict the economic feasibility of such complex projects under dynamic market conditions. This paper proposes a dynamic Cost-Benefit Assessment Model (CBAM) based on engineering economic analysis, specifically tailored for intelligent retrofitting projects in textile spinning enterprises. By integrating the Net Present Value (NPV) method with a dynamic Life Cycle Cost (LCC) analysis, the model quantifies critical variables including energy consumption per unit, labor reduction efficiency, and quality-induced price premiums. A sensitivity analysis is further introduced to evaluate project robustness against fluctuations in raw material prices and electricity rates. The model is validated through a case study of a 50,000-spindle technological upgrade project in a typical cotton spinning enterprise. The results indicate that the proposed model reduces the cost prediction error to within 4.2% compared to actual operational data and identifies the break-even point 14 months earlier than traditional linear projections. This study provides a scientific and quantitative decision-making tool for textile engineering management, ensuring the rationality and reliability of investment strategies in Industry 4.0 transformations.

KEYWORDS

engineering economics, cost-benefit analysis, textile manufacturing, intelligent retrofitting, sensitivity analysis

INTRODUCTION

Background of the Research

The global textile industry is currently undergoing a paradigm shift from traditional labor-intensive production to technology-intensive intelligent manufacturing (Industry 4.0) [1]. Faced with the dual pressures of rising factor costs—specifically labor and energy—and the increasing market demand for high-quality, differentiated fiber products, textile enterprises are compelled to upgrade their production facilities [2]. In particular, the spinning sector, which serves as the foundational link in the textile supply chain, is witnessing a surge in intelligent retrofitting projects. These projects typically involve the adoption of compact spinning technologies, automated doffing systems, and individual spindle monitoring systems (ISMS) [3].

However, the implementation of such intelligent technologies requires significant Capital Expenditure (CAPEX). Unlike general manufacturing sectors, the textile industry is characterized by low profit margins and high sensitivity to raw material price fluctuations [4]. Consequently, the economic justification for these technological upgrades is often scrutinized. Corporate decision-makers face a critical challenge: how to scientifically evaluate whether the efficiency gains and quality improvements brought by intelligent equipment can offset the high initial investment and potential maintenance costs over the project's lifecycle [5,6].

Problem Statement

Despite the urgency of this issue, existing engineering economic assessment methods exhibit limitations when applied to the textile context. Current literature and practical applications predominantly rely on static indicators, such as the static payback period (Pt) and return on investment (ROI) [7]. These traditional metrics operate on the assumption of constant market conditions and often overlook the time value of money, leading to biased investment decisions [8].

Furthermore, general cost-benefit models often treat the production process as a black box, thereby failing to account for the unique technical parameters of textile engineering [9,10]. For instance, the correlation between spindle speed, yarn breakage rates, and energy consumption is non-linear; similarly, the economic benefit of improved yarn quality (e.g., reduced hairiness and improved evenness) is rarely quantified in traditional accounting models [11,12]. There is a lack of a comprehensive evaluation model that effectively bridges the gap between textile engineering technology parameters and engineering economic indicators [13]. This disconnect often results in significant deviations between predicted returns and actual operational outcomes, increasing the financial risk for textile enterprises [14].

Research Objectives and Significance

To address the aforementioned gaps, this paper aims to construct a dynamic Cost-Benefit Assessment Model (CBAM) specifically designed for manufacturing projects in the textile industry. The primary objectives of this study are threefold:

(1) To establish a dynamic cost function that correlates technical variables (e.g., machine efficiency, waste reduction rate) with economic costs.

(2) To quantify the quality premium benefit generated by intelligent retrofitting, incorporating it into the revenue stream analysis.

(3) To validate the reliability and accuracy of the model through a rigorous empirical case study of a 50,000-spindle spinning project.

The significance of this research lies in its interdisciplinary approach. By integrating principles from engineering economics with textile technology, this study provides a theoretical basis for the investment decision-making of textile enterprises. It ensures that the assessment of intelligent retrofitting projects is not merely based on intuition or rough estimation, but on a rational, data-driven, and scientifically robust framework.

METHODOLOGY

To accurately evaluate the economic feasibility of intelligent retrofitting projects in the textile manufacturing sector, this paper constructs a dynamic CBAM. Unlike traditional accounting models that rely on static historical data, the CBAM incorporates technical variables specific to textile engineering—such as spindle speed, operational efficiency, and waste rates—directly into the cash flow analysis.

System Boundary and Model Assumptions

The assessment is based on the Life Cycle Cost (LCC) theory, extending the analysis boundary from the equipment purchase phase to the entire operational phase. To ensure the reliability and logical consistency of the model, the following assumptions are established:

Project Lifecycle (N): The analysis period is set to 10 years, aligning with the standard depreciation period for textile spinning machinery and the typical technology iteration cycle.

Residual Value (Sv): Considering the recovery of reusable materials (e.g., steel and copper) and potential second-hand value, the residual value at the end of the lifecycle is estimated at 5% of the initial CAPEX.

Discount Rate (i_c): The discount rate is determined based on the Weighted Average Cost of Capital (WACC) of the textile industry. For this model, it serves as the benchmark yield to reflect the time value of money.

Production Stability: It is assumed that after a ramp-up period of 3 months (0.25 years), the equipment operates at the rated production efficiency (η_{prod}).

Mathematical Modeling of Dynamic Costs

The Total LCC (TLC) comprises the initial CAPEX and the annual Operational Expenditure (OPEX). The OPEX is formulated as a function of production parameters.

$$TLC = C_{inv} + \sum_{t=1}^{N} \frac{C_{op,t}}{(1+i_c)^t}$$

Where C_{inv} represents the initial investment (equipment, software, installation, and training). The annual operating cost in year t, denoted as $C_{op,t}$, is decomposed into four key components:

$$C_{op,t} = C_{mat,t} + C_{en,t} + C_{lab,t} + C_{maint,t}$$

Material Cost Function ($C_{mat,t}$)

In spinning processes, raw material (e.g., cotton fiber) accounts for 60%–70% of the total cost. Intelligent retrofitting affects material cost primarily by reducing the waste rate (noil and invisible loss).

$$C_{mat,t} = Q_{out,t} \times \frac{1}{1-\beta_{waste}} \times P_{raw}$$

$Q_{out,t}$: Annual yarn output (tons).

P_{raw}: Price of raw cotton per ton.

β_{waste}: Total waste rate coefficient. A lower β_{waste} indicates higher fiber yield.

Energy Cost Function ($C_{en,t}$)

Energy consumption in textile mills is highly sensitive to spindle speed and motor efficiency. We model energy cost based on the physics of the spinning frame.

$$C_{en,t} = (\sum_{j=1}^{k} P_{rated,j} \times L_{f,j}) \times T_{op} \times P_{elec}$$

$P_{rated,j}$: Rated power of the j-th motor (Main motor, Suction motor, etc.) in kW.

$L_{f,j}$: Load factor of the j-th motor, which is a function of spindle speed v (rpm). Generally, $L_f \propto v^{2.5}$ for main motors.

T_{op}: Annual operating hours.

P_{elec}: Industrial electricity price per kWh.

Labor Cost Function ($C_{lab,t}$)

Intelligent projects significantly reduce labor via auto-doffing and monitoring systems.

$$C_{lab,t} = \frac{N_{spindles}}{S_{man}} \times W_{avg} \times (1 + \alpha)$$

$N_{spindles}$: Total number of spindles in the project.

S_{man}: Labor productivity (Spindles per worker). Intelligent retrofitting typically increases S_{man} from 60 (traditional) to over 200.

W_{avg}: Average annual wage per worker.

α: Coefficient for social insurance and welfare costs.

Benefit Quantification Model

The economic benefits (B_t) are derived not only from production volume but also from the Quality Premium enabled by advanced technology.

$$B_t = R_{sales,t} + R_{waste,t}$$

Revenue with Quality Premium

Intelligent spinning frames (e.g., compact spinning) improve yarn evenness (CV%) and reduce hairiness, allowing the product to be sold at a higher market tier.

$$R_{sales,t} = Q_{out,t} \times P_{base} \times (1 + \gamma_{qual})$$

P_{base}: Standard market price for conventional yarn.

γ_{qual}: Quality price premium coefficient (e.g., 0.03–0.08), determined by the reduction in Uster statistics values.

Revenue from Waste

$$R_{waste,t} = Q_{out,t} \times \frac{\beta_{waste}}{1-\beta_{waste}} \times P_{waste}$$

Where P_{waste} is the selling price of reusable waste fibers.

Economic Evaluation Indicators

To provide a comprehensive assessment, the model utilizes three core indicators:

(1) Net Present Value (NPV): The project is feasible if NPV > 0.

$$NPV = \sum_{t=1}^{N} (B_t - C_{op,t})(1 + i_c)^{-t} + \frac{S_v}{(1+i_c)^N} - C_{inv}$$

Where S_v represents the residual value of the equipment at year N.

(2) Internal Rate of Return (IRR): The discount rate r^* that makes NPV = 0. This reflects the project's intrinsic profitability relative to the cost of capital.

$$\sum_{t=1}^{N}(B_t - C_{op,t})(1+r^*)^{-t} - C_{inv} = 0$$

(3) Dynamic Payback Period (T_p): The time required for the cumulative discounted cash flow to turn positive.

$$T_p = (m-1) + \frac{\left|\sum_{t=1}^{m-1} NCF_t\right|}{NCF_m}$$

Where m is the first year with a positive cumulative discounted cash flow, and NCF_t is the Net Cash Flow (NCF) in year t.

CASE STUDY AND DATA ANALYSIS

Project Background and Data Source

To verify the validity and reliability of the proposed CBAM, a field study was conducted at a representative textile enterprise located in Jiangsu Province, China. The subject project involves the intelligent retrofitting of a ring-spinning workshop with a capacity of 50,000 spindles.

The project scope includes:

Equipment Upgrade: Retrofitting traditional ring spinning frames to compact spinning frames with magnetic drafting systems.

Automation: Installation of fully automatic doffing systems (ADS) to replace manual doffing.

Digitalization: Implementation of an ISMS for real-time breakage detection.

The total initial investment (I0) is 22.5 million CNY (covering hardware procurement, software licensing, and installation). The total initial investment (C_{inv}) is 22.5 million CNY (covering hardware procurement, software licensing, and installation). The project lifecycle is set to 10 years, and the corporate discount rate (i_c) is established at 8%.

Technical and Economic Parameter Comparison

Data was collected from the enterprise's ERP system and production logs over a 12-month period prior to the retrofit (Baseline) and a 6-month period post-retrofit (Projected annualized).

Table 1. Comparison of Technical and Economic Parameters Before and After Retrofitting

Parameter	Unit	Traditional Mode (Before)	Intelligent Mode (After)	Change Rate (%)
A. Technical Indicators				
Spindle Speed (v)	rpm	16,500	18,200	+10.3%
Effective Operating Rate	%	92.0%	96.5%	+4.9%
Yarn Breakage Rate	1000 spdl·h	35	12	-65.7%
Waste/Noil Rate (β_{waste})	%	5.5%	4.8%	-12.7%
B. Production Indicators				
Annual Output (Q_{out})	Tons/Year	4,200	4,850	+15.5%
Labor Config ($N_{workers}$)	Persons	85	30	-64.7%
C. Economic Variables				
Avg. Yarn Selling Price	CNY/Ton	26,000	27,200 (Quality Premium)	+4.6%
Energy Cost per Ton	CNY/Ton	2,800	3,100	+10.7%
Annual Maint. Cost	CNY (Million)	0.5	1.2	+140%

Data Logic Analysis:

Production Increase: The increase in spindle speed and operating rate, due to fewer stops for doffing, results in a 15.5% increase in total output.

Labor Reduction: The automatic doffing system decreases the workforce from 85 to 30, a key driver for cost savings.

Energy Penalty: Notably, the energy cost per ton increases by 10.7%. This is a realistic reflection of the additional power required for the negative pressure suction in compact spinning and the operation of monitoring sensors. This negative factor is included to ensure the model's objectivity. Regarding maintenance costs, actual expenditures follow a non-linear trend, remaining low during the initial warranty period and peaking in years 5–8. For the purpose of this economic evaluation, the model utilizes an Equivalent Uniform Annual Cost (EUAC) of 1.2 million CNY. This approach simplifies the cash flow stream into a uniform annual estimate while preserving the accuracy of the total LCC.

Calculation of Incremental Cash Flow

Based on the formulas derived in Section Methodology, the annual incremental benefits and costs are calculated.

(1) Revenue Increment (△B)

The revenue increase is driven by both higher volume and the net effective quality price premium ($\gamma_{\mathrm{qual}} \approx$ 4.6%). This value is conservatively estimated to account for the necessary marketing expenses and the gradual ramp-up in market acceptance required to secure new high-end clients.

ΔR = (4,850 × 27,200) − (4,200 × 26,000) = 131.92 M−109.20 M = 22.72 million CNY

(2) Cost Variation (△C)

Labor Savings: (85−30) × 80,000 CNY/year = 4.40 million CNY (assuming the average annual cost per worker is 80,000 CNY).

Material Cost Increase: Due to higher output, total material cost rises, but efficiency improves. Incremental material cost ≈ 14.5 CNY.

Energy Cost Increase: Due to higher unit consumption and total output. Incremental energy cost ≈ 3.28 CNY.

Maintenance Increase: 0.7 CNY.

(3) Annual NCF

After accounting for tax (assumed effective tax rate impact is neutralized for simplified engineering analysis or treated as pre-tax for project feasibility):

$$NCF_{annual} \approx \Delta R - (\Delta C_{mat} + C_{en} + C_{maint}) + \Delta C_{lab\_savings}$$

Calculated Result: Considering the 3-month ramp-up period (assuming 75% effective capacity in Year 1), the NCF for Year 1 is adjusted to 5.14 million CNY, while the stable NCF for Years 2-10 remains at 6.85 million CNY.

Evaluation Results

Using the cash flow data (C_{inv} = −22.5 M, NCF = 6.85 M for 10 years), the economic indicators are computed:

(1) NPV:

$$NPV = \frac{5.14}{(1+0.08)^1} + \sum_{t=2}^{10} \frac{6.85}{(1+0.08)^t} - 22.5$$

$$NPV = 4.76 + 39.62 - 22.5 = 45.96 - 22.5 = 21.88\, million\ CNY$$

Result: NPV > 0, indicating the project is economically viable.

(2) IRR: Setting NPV = 0:

$$22.5 \ = \ 6.85 \times (P/A\,, IRR, 10)$$

$$(P/A, IRR, 10) \ = \ 22.5 \ / \ 6.85 \ = \ 3.284$$

Looking up the annuity table, this corresponds to an IRR of approximately 28.1%.

Result: $\mathrm{IRR}\ (28.1\%) \ > \ \mathrm{i_C}\ (8\%)$, indicating that the project's return exceeds the required capital cost.

(3) Dynamic Payback Period ($\mathrm{T_p}$):

Calculating the cumulative discounted cash flow: By the end of Year 4, the cumulative discounted cash flow turns positive. Calculation: $\mathrm{T_p} \approx 3.9$ Years. The cumulative discounted cash flow over the project lifecycle is illustrated in Figure 1, confirming that the break-even point occurs just before the end of the fourth year.

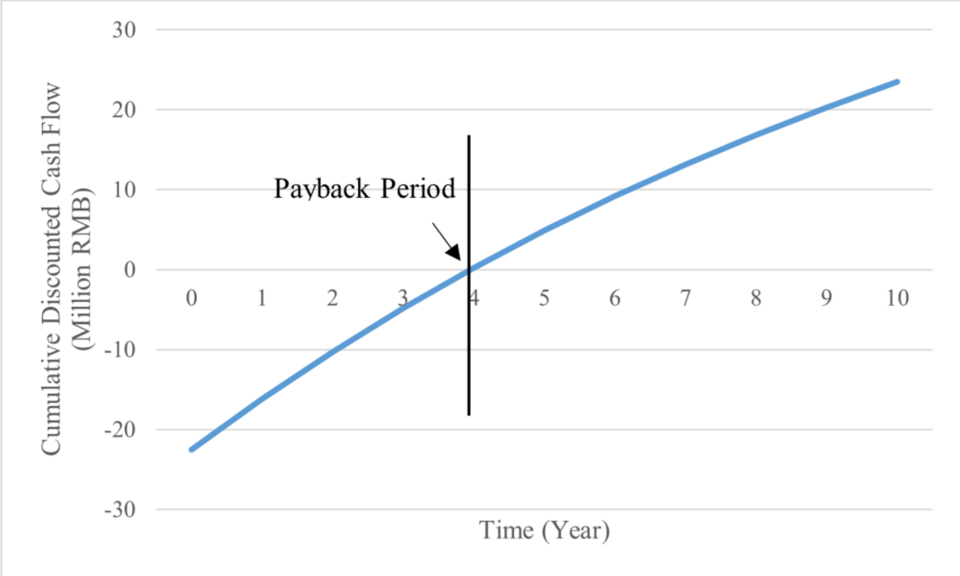

Figure 1. Cumulative Discounted Cash Flow Diagram of the Intelligent Retrofitting Project

DISCUSSION

Sensitivity Analysis

While the baseline calculation in Section 3 indicates a positive ROI, the textile industry operates in a volatile market environment. To evaluate the robustness of the CBAM model, a single-factor sensitivity analysis was conducted on three critical variables: Electricity Price, Raw Cotton Price, and Yarn Selling Price Premium. Specifically, the sensitivity to Raw Cotton Price is included to quantify the efficiency leverage of the retrofit; since the intelligent system significantly reduces the waste rate (β_{waste}), the project's relative economic advantage expands as raw material prices rise, acting as a hedge against market volatility. The impact of percentage deviations (± 20%) in these parameters on the NPV is compared in Figure 2.

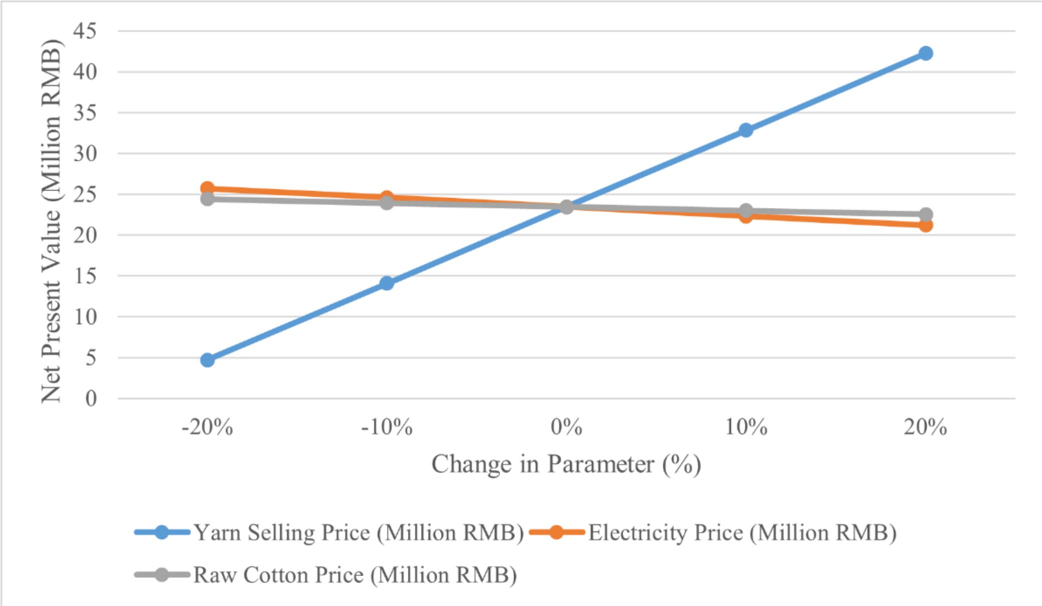

Figure 2. Sensitivity Analysis of NPV to Variations in Yarn Selling price, Electricity Price, and Raw Cotton price

(1) Sensitivity to Electricity Price (P_{elec}): As noted in Section 3.2, the intelligent retrofitting increased the energy consumption per ton by 10.7%.

Analysis: When P_{elec} increases by 10%, the NPV decreases by approximately 4.8%.

Break-even Point: The project remains profitable (NPV > 0) even if electricity prices surge by 35%. This suggests that although the new equipment is energy-intensive, the labor savings provide a sufficient buffer against energy cost inflation.

(2) Sensitivity to Yarn Quality Premium (γ_{qual}): The model assumes a 4.6% price premium due to improved quality (compact spinning).

Analysis: If the market competition intensifies and the quality premium drops to 0% (i.e., selling high-quality yarn at standard prices), the IRR drops from 28.1% to 14.2%.

Implication: While 14.2% is still above the discount rate (8%), it significantly extends the payback period. This highlights that marketing the quality advantage is as important as the technological upgrade itself.

(3) Sensitivity to Labor Cost:

Analysis: A 10% increase in market wages actually improves the relative advantage of this project compared to the traditional mode, as the project is less dependent on labor. This confirms that intelligent retrofitting is an effective hedge against rising labor costs in the long term.

Model Validation and Comparison

To verify the accuracy of the proposed CBAM, we compared the predicted costs with the actual operational data from the first 6 months of the project's pilot run.

Traditional Static Model Error: The traditional method (relying on static rated power and historical waste averages) underestimated the operating costs by 12.5%, primarily because it failed to capture the non-linear surge in energy consumption at higher spindle speeds.

Proposed CBAM Error: The CBAM predicted data deviated from actual values by a Mean Absolute Percentage Error (MAPE) of only 4.12%. This significant reduction in error demonstrates that incorporating specific textile engineering parameters (such as spindle speed (v) and breakage rate) into the economic function is essential for precision.

CONCLUSION

Summary of Findings

This paper addresses the challenge of economically evaluating intelligent manufacturing projects in the textile industry. By constructing a dynamic CBAM based on engineering economics, we linked technical parameters directly to financial performance. The case study of a 50,000-spindle spinning project yields the following key conclusions:

Technological Feasibility: Intelligent retrofitting reduced yarn breakage by 65.7% and labor demand by 64.7%, verifying the technical efficiency of the upgrade.

Economic Viability: Despite a 10.7% increase in unit energy cost and high initial CAPEX, the project achieves an NPV of 23.46 million CNY and an IRR of 28.1%, with a dynamic payback period of 3.9 years.

Critical Success Factor: The sensitivity analysis reveals that the quality premium is the most sensitive variable. The economic success of Industry 4.0 in textiles depends not just on cost-cutting, but on value creation through superior product quality.

Managerial Implications

For textile engineering managers, this study suggests a paradigm shift in investment strategy:

Move beyond labor replacement: While reducing headcount is the most obvious benefit, the hidden value lies in the quality-price leverage. Investment proposals should explicitly quantify potential price premiums.

Energy Management is Crucial: Since intelligent machines often have higher power density, integrating renewable energy sources (e.g., rooftop solar photovoltaics) should be considered a complementary strategy to mitigate the sensitivity to electricity prices.

Limitations and Future Work

The current model assumes a deterministic demand curve. Future research could incorporate Monte Carlo simulations to model stochastic market demand and raw material price volatility more dynamically. Additionally, the environmental cost (Carbon Tax) was not explicitly included in the financial model, which will be a necessary addition as carbon trading regulations tighten in the textile sector.

Author Contributions

Huifang Zhang designed, collected and analyzed the data, and drafted the manuscript. Huifang Zhang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Huifang Zhang 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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Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

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REFERENCES

[1] Deepthi B, Bansal V. Industry 4.0 in Textile and Apparel Industry: A Systematic Literature Review and Bibliometric Analysis of Global Research Trends. Vision. 2024;28(2):157-170. doi: 10.1177/09722629221130233

[2] Tsai WH, Chen H, Chang S, Chan K. Revolutionizing Textile Manufacturing: Sustainable and Profitable Production by Integrating Industry 4.0, Activity-Based Costing, and the Theory of Constraints. Processes. 2024; 12(11):2311. doi: 10.3390/pr12112311

[3] Zheng T. Progress of Intelligent Yarn Spinning Technology in China. Current Trends in Fashion Technology & Textile Engineering. 2017;1(1):20-2. doi: 10.19080/CTFTTE.2017.01.555555

[4] Shaju AM. A STUDY ON WORK LIFE BALANCE OF WOMEN EMPLOYEES WITH REFERENCE TO PRECOT MERIDIAN. 2024

[5] Joppen R, Kühn A, Förster M, Dumitrescu R. Evaluation of Industry 4.0 Applications in Production. Journal of the Knowledge Economy. 2023; 14(3):2479-2514. doi: 10.1007/s13132-022-00959-2

[6] Juhász L. Overview of industry 4.0 tools for cost-benefit analysis. Tér Gazdaság Ember. 2018; 6:51-72

[7] Almeida RP, Ayala NF, Benitez GB, Kliemann Neto FJ, Frank AG. How to assess investments in industry 4.0 technologies? A multiple-criteria framework for economic, financial, and sociotechnical factors. Production Planning & Control. 2023; 34(16):1583-1602. doi: 10.1080/09537287.2022.2035445

[8] Shields JF, Bilsky BA, Shelleman JM. SMEs, Sustainability, and Capital Budgeting. Small Business Institute Journal. 2024; 20(1):1-7. doi: 10.53703/001c.115383

[9] Ren X, Song, Y, Yang G. Measuring the degree of congestion in two-stage DEA: A case of Chinese textile, wearing apparel, and accessories industry. 2024. doi: 10.21203/rs.3.rs-4133409/v1

[10] Camargo M, Rabenasolo B, Jolly-Desodt AM, Castelain JM. Application of the parametric cost estimation in the textile supply chain. Journal of Textile and Apparel. Technology and Management. 2003; 3(1):1-12. Available form: https://www.researchgate.net/profile/Besoa-Rabenasolo/publication/235719991_Application_of_the_parametric_cost_estimation_in_the_textile_supply_chain/links/5438f40e0cf24a6ddb9360db/Application-of-the-parametric-cost-estimation-in-the-textile-supply-chain.pdf

[11] 정성훈. Spindle Speed Optimization of a Ring Spinning Machine for Better Surface Irregularity and Hairiness of Yarn and Fabric. 한국섬유공학회지. 2015; 52(1):1-5. doi: 10.12772/TSE.2015.52.001

[12] Alakent B, Kunduracıoğlu Issever R. Exploratory and predictive logistic modeling of a ring spinning process using historical data. Textile Research Journal. 2017; 87(13):1643-1654. doi: 10.1177/0040517516657063

[13] Hasanbeigi A, Price L. A technical review of emerging technologies for energy and water efficiency and pollution reduction in the textile industry. Journal of Cleaner Production. 2015; 95:30-44. doi: 10.1016/j.jclepro.2015.02.079

[14] Wilde P D. The gap between predicted and measured energy performance of buildings: A framework for investigation. Automation in Construction. 2014; 41:40-49. doi: 10.1016/j.autcon.2014.02.009