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Textile Manufacturing Carbon Emission Analysis Method Based on Holographic Process Model

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Abstract: The textile industry, while creating material wealth, also exerts a significant impact on the environment. Particularly in the textile manufacturing phase, which is the most energy-intensive phase throughout the product lifecycle, the problem of high energy usage is increasingly notable. Nevertheless, current analyses of carbon emissions in textile manufacturing emphasize the dynamic temporal characteristics while failing to adequately consider critical information such as material flows and energy consumption. A carbon emission analysis method based on a holographic process model (HPM) is proposed to address these issues. First, the system boundary in the textile manufacturing is defined, and the characteristics of carbon emissions are analyzed. Next, an HPM based on the object-centric Petri net (OCPN) is constructed, and simulation experiments are conducted on three different scenarios in the textile manufacturing. Subsequently, the constructed HPM is utilized to achieve a multi-perspective analysis of carbon emissions. Finally, the feasibility of the method is verified by using the production data of pure cotton products from a certain textile manufacturing enterprise. The results indicate that this method can analyze the impact of various factors on the carbon emissions of pure cotton product production, and by applying targeted optimization strategies, carbon emissions have been reduced by nearly 20%. This contributes to propelling the textile manufacturing industry toward sustainable development.

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0 Introduction

As global climate change becomes increasingly severe, especially that caused by CO_2, it has become one of the serious challenges faced by the development of human society. Therefore, carbon emission analysis has become particularly important in various industries and has also become a hot topic in the field of academic research[1]. As a traditional pillar industry of the economy, the textile industry's energy consumption and carbon emissions have a significant impact on the environment. This impact cannot be ignored. In the face of the global trend toward sustainable development, the textile industry is increasingly attaching importance to carbon emission analysis in order to achieve carbon neutrality goals[2]. Most importantly, an accurate assessment of the carbon emissions of the textile industry can not only help textile companies gain a foothold in the global textile trade market but also provide necessary reference data for achieving future emission reduction targets[3]. Huang et al.[4] evaluated the carbon emissions of the entire lifecycle of the textile industry, thereby enhancing the environmental value of textile products and subsequently proposing suggestions for energy conservation and emission reduction to achieve the sustainable development goals of the textile industry. Peters et al.[5] indicated that the carbon emission metric takes into account the relative importance of different greenhouse gases and allows for the analysis of a product's carbon footprint from a lifecycle perspective.

Carbon emissions produced during the textile manufacturing phase (including both agricultural and industrial production) account for the highest proportion in the entire lifecycle of textiles, exceeding 90%. Among these, energy consumption, particularly electricity consumption, is the primary contributing factor to carbon emissions[6]. The textile manufacturing process includes six stages: spinning, weaving, pretreatment, dyeing, post-treatment, and garment manufacturing. These stages are characterized by a long, complex, and fragmented manufacturing process with low transparency, making the tracking of carbon emissions in this sector particularly challenging. To address these challenges, researchers have attempted to use the life cycle assessment (LCA) method to optimize the textile manufacturing process and

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enhance the ecological efficiency of the supply chain, thereby assisting textile companies in making more environmentally friendly and economical decisions in material selection and procurement[7]. Bianco et al.[8] used LCA to track the carbon emissions of the knitting, cutting, and sewing stages at an Italian company, and the results showed that a single T-shirt can generate 11.7 kg carbon dioxide equivalent (CO_2 eq). By evaluating the influence on various indicators, a deeper understanding of the environmental impacts related to the diverse stages of the T-shirt's lifecycle was achieved. He et al.[9] introduced four groups of measures in 12 scenarios to explore low-carbon pathways of polyamide textile manufacturing.

In the textile manufacturing industry, there is a wide variety of textile manufacturing with different production processes, which makes it complex to establish a unified carbon emission analysis model for the production of cotton garments[10]. Tracking the carbon emissions of cotton garments involves the flow of a large number of materials (such as raw materials and chemicals) and energy (such as electricity and heat), and accurately describing these flows is also a challenging issue. Most importantly, in the actual production process of textile manufacturing, multiple products are produced simultaneously every day, and the production volume of each product may vary, which means that these dynamic characteristics need to be taken into account when conducting carbon emission analysis. Petri nets[11], as visual representation methods, are effective at characterizing dynamic system behavior and can clearly describe the fluctuations in the production volume and product changes, adapting to the needs of different production scenarios. They have been widely used in carbon emission modeling and analysis[12]. Priya et al.[13] used a generalized stochastic Petri net (GSPN) to simulate the spinning process, combining reinforcement learning to help cotton textile factories manage and optimize energy usage. The data-driven hybrid Petri net (DDHPN), integrated with digital twin technology, has achieved more accurate prediction of energy behavior, providing an effective means for energy management in the digital transformation of manufacturing industries[14]. Shi et al.[15] proposed a method for analyzing the greenhouse gas emissions in product remanufacturing based on Petri nets, and quantitatively analyzed the different greenhouse gas emissions in the remanufacturing process of diesel engines. Peng et al.[16] used the transition in Petri nets to simulate the dynamic energy consumption behavior of the cylinder remanufacturing process, which could help remanufacturing companies to develop potential energy efficiency improvement strategies.

However, when using Petri nets to establish carbon emission models, these models can only provide a carbon emission perspective, resulting in the flattening of information, such as the fabrics used in products and the relationships between different products. This valuable information is redundant when tracking the carbon emissions of a single product[17]. In actual textile manufacturing, the daily production activities vary, and there is a wide variety of fabrics used, such as cotton, hemp, and wool. Each product has different production processes, and the key factors affecting the carbon emissions of textile manufacturing are the types of fabrics used and the corresponding production processes. These dynamic characteristics make it complex to establish a unified carbon emission analysis model for the textile manufacturing process[3]. Most importantly, in the actual production process of textile manufacturing, multiple products are produced simultaneously every day, and the production volume of each product changes, so when tracking the carbon emissions, it is necessary to incorporate the dynamic characteristics of different products.

To address the issue of data flattening when using Petri nets, markers are added to the Petri nets to generate colored Petri nets[18-19]. Van der Aalst et al.[20] proposed a method that could handle processes more comprehensively and could observe multiple object types and their interrelationships. This method is known as the object-centric Petri net (OCPN). Graves et al.[21] highlighted the potential of process mining for assessing business process sustainability, as well as its ability to support data-driven decision-making and targeted improvements. Delgado et al.[22] suggested that a sustainable dimension should be incorporated when evaluating process discovery algorithms. Brehm et al.[23] proposed that through process mining, carbon emission data can be integrated into OCPN to create a more transparent production process.

Due to the increasing demand for product customization, the production process of textile manufacturing has also become more diverse, necessitating the consideration of more dynamic factors when modeling and analyzing carbon emissions. This study proposes a holographic process model (HPM) based on OCPN, which can comprehensively analyze energy consumption bottlenecks in different products and support simulation in various execution scenarios.

The challenges of this study include data collection and integration, the construction of the HPM, and the analysis of multivariable carbon emissions. This leads to the following two research questions. 1) How to construct a carbon emission analysis model that includes multiple perspectives and complete information to adapt to the input requirements of different algorithms, and integrate the key dimension of carbon emissions during the model construction process? 2) How to utilize the HPM for carbon emission analysis and effectively utilize the various types of information contained in the HPM?

In response to these challenges, this study presents two key contributions: 1) an HPM based on OCPN is proposed, which retains valuable information and provides strong support for subsequent algorithms; 2) an energy consumption analysis method based on the HPM is proposed, which combines process mining with other algorithms to provide an effective energy management tool for textile manufacturing.

The study is structured as follows. In Section 1, the characteristics of carbon emissions in textile manufacturing are introduced. In Section 2, a detailed exposition of the energy consumption analysis method based on the HPM is presented. In Section 3, the application of the method through case analysis is presented. In Section 4, the study is summarized, and an outline of future work is provided.

1 Carbon Emission Analysis of Textile Manufacturing

The textile manufacturing process consists of six stages: spinning, weaving, pretreatment, dyeing, post-treatment, and garment manufacturing, as shown in Fig. 1. During the textile manufacturing, raw materials (such as size, dyes, and auxiliaries) and energy resources (like electricity, water, steam, and oil) are consumed, all of which contribute to carbon emissions.

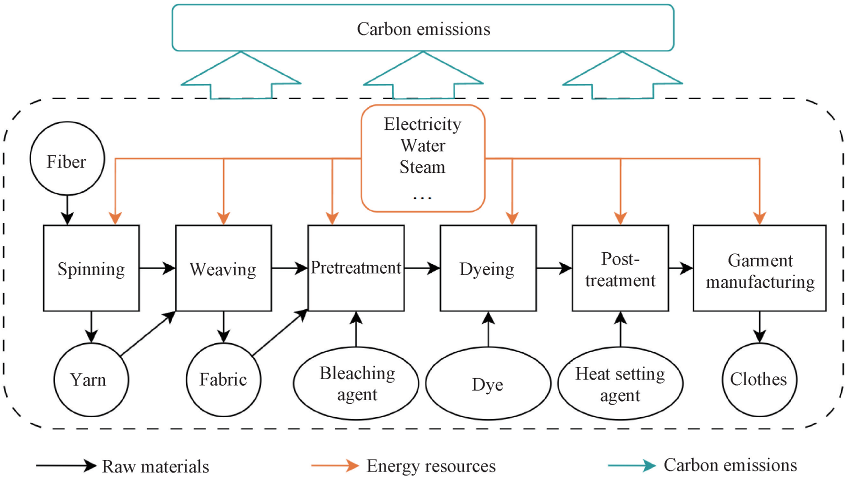


Fig. 1 Textile manufacturing process

When calculating carbon emissions, the internationally accepted emission factor method is employed. The emission factor method refers to the *National Greenhouse Gas Inventories Guidelines* compiled by the United Nations Framework Convention on Climate Change (UNFCCC)[24], which provides detailed methods for calculating carbon emissions and has become an internationally recognized and commonly used approach for carbon emission assessment. The scope of its research includes the industrial sector. The emission factor method involves the use of activity data and an emission factor. Here, activity data represents the scale of human activity, while the emission factor is the coefficient used to quantify the associated emissions or removals per unit of that activity. A commonly used formula for calculating carbon emissions is

$$E_c = \sum_{i=1}^{q} (A_i \times E_i), \tag{1}$$

where E_c represents the total amount of carbon emissions; q represents the total number of energy types; A_i represents the ith energy consumption factor; E_i represents the ith energy emission.

The system boundary of textile manufacturing encompasses various conversion and consumption of energy (energy flow), various material inputs and outputs (material flow), and substantial carbon emissions (carbon emission flow) during these processes, as shown in Fig. 2.

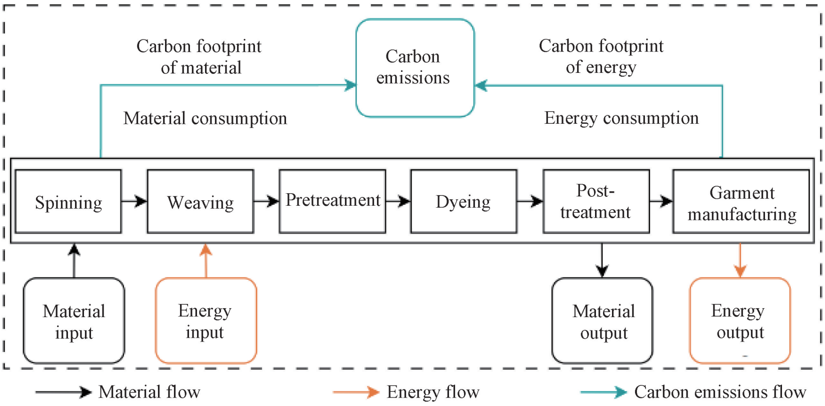


Fig. 2 System boundary of textile manufacturing

1) Energy flow

In accordance with ISO 14067[25], which provides the carbon emission analysis with universality, common energy sources encompass primary energy sources (raw coal, natural gas, and biomass energy, etc.), secondary energy (primarily electricity), and energy-consuming working substances (tap water, compressed air, etc.). The energy consumption in the textile manufacturing includes electricity, compressed air, tap water, etc., with electricity being the main source. By converting the aforementioned energy sources into comprehensive energy consumption, the power consumption per unit of time is expressed as

$$e(t) = \sum_{i=1}^{n} e_i, \tag{2}$$

where n represents the total number of process steps; e_i represents the electrical energy consumption in the ith process step; $e(t)$ represents the comprehensive energy consumption per unit of time t, which can be expressed as a constant or a function.

2) Material flow

The materials consumed during the production of textile manufacturing mainly include natural fibers, synthetic chemical fibers, dyes, additives, etc. The material consumption per unit of time is expressed as

$$m(t) = \sum_{i=1}^{n} \sum_{j=1}^{k} m_i^j, \tag{3}$$

where j represents the jth material; k represents the total number of material types; m_i^j represents the jth material consumption in the ith process step; $m(t)$ represents the comprehensive energy consumption, which can be expressed as a constant or a function.

3) Carbon emission flow

During the textile manufacturing, the transmission and conversion of energy, the processing of raw materials and auxiliary materials, as well as the recycling of materials, are all accompanied by the generation of carbon emissions. The carbon emissions are primarily composed of energy-related carbon emissions and material-related carbon emissions. By analyzing the characteristics of the energy and material flows in the textile manufacturing, the carbon emission flow characteristics of the textile manufacturing can be obtained.

In textile manufacturing, the majority of processing is carried out by machines, with the entire machine processing primarily relying on electrical energy consumption, resulting in indirect carbon emissions. At the same time, there is also a consumption of materials during the textile manufacturing. For instance, the size and steam are used in the weaving stage, and water, dyes, and additives are required in the dyeing stage. The consumption of these materials leads to the emission of greenhouse gases such as CO_2. Furthermore, the textile manufacturing generates waste, and the disposal of this waste results in the discharge of greenhouse gases. Within the time period T, the total carbon emission flow of the pure cotton product production line can be calculated as

$$\begin{aligned} E_{\mathrm{c,\,total}} &= E_{\mathrm{c,\,E}} + E_{\mathrm{c,\,M}} = \int_0^T \alpha \times e(t)\,\mathrm{d}t + \int_0^T \omega \times m(t)\,\mathrm{d}t \\ &= \int_0^T \sum_{i=1}^{n} \alpha_i \times e_i \times \mathrm{d}t + \int_0^T \sum_{i=1}^{n} \sum_{j=1}^{k} \omega_i \times m_i^j \times \mathrm{d}t, \end{aligned} \tag{4}$$

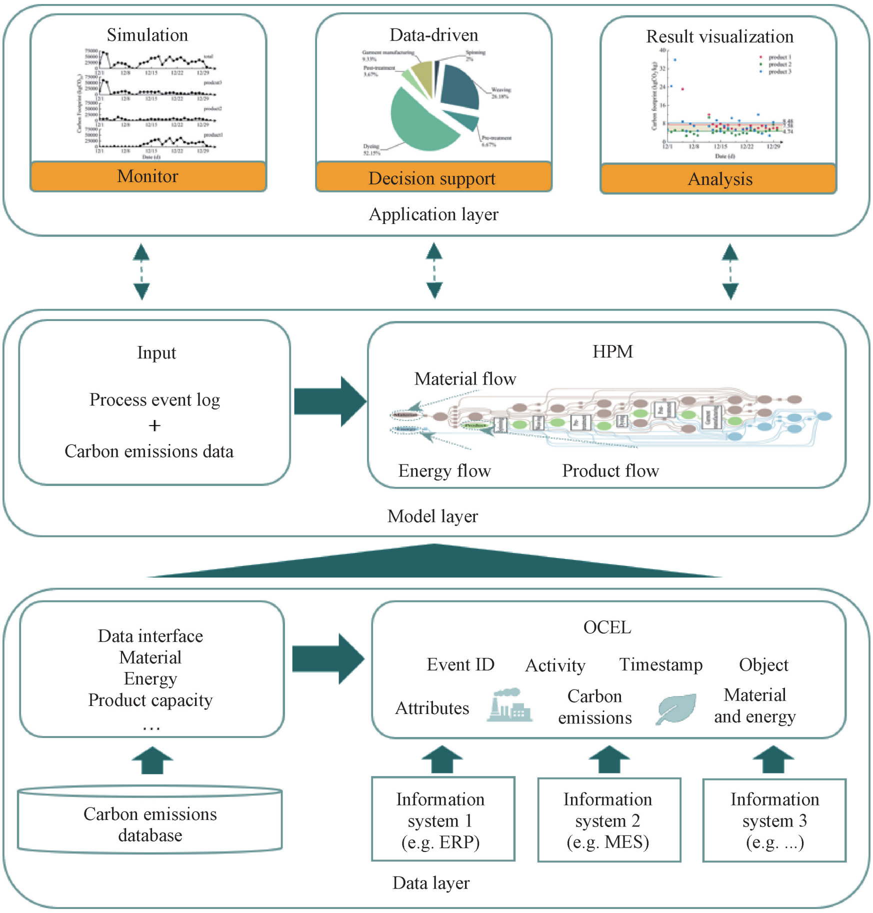
where $E_{\mathrm{c,\,total}}$, $E_{\mathrm{c,\,E}}$, and $E_{\mathrm{c,\,M}}$ represent comprehensive carbon emissions, energy-related carbon emissions, and material-related carbon emissions, respectively; α_i and ω_i respectively represent the carbon emission coefficients for the ith type of energy and material.

2 Carbon Emission Analysis Based on HPM

By utilizing the strong coupling characteristic between carbon emission and the process in textile manufacturing, we propose a carbon emission analysis method based on an HPM. Figure 3 shows the architecture of the method.

When constructing a carbon emission analysis model, it is necessary to distinguish these data. The HPM introduced in this study is capable of presenting a complete overview of carbon emissions throughout the textile manufacturing process, which offers a scientific basis for real-time monitoring and the development of emission reduction strategies. In the HPM, the energy flow and material flow are displayed as different object types, while the product flow represents the carbon emission flow tightly coupled with the production process. Moreover, the HPM thoroughly examines the carbon emission features within material, energy and product flows, aiding in the identification of critical carbon emission steps and those that necessitate optimization.

By integrating carbon emission data with process event logs, an event log containing carbon emission information is constructed. Subsequently, the event log is converted into an object-centric event log (OCEL)[26], facilitating the extraction of OCPN by using object-centric process mining (OCPM) techniques[27].



EPR—the enterprise resource planning system; MES—the manufacturing execution system.

Fig. 3 Overview of carbon emission analysis method framework based on HPM

2.1 Definition of OCPN

Definition 1: OCEL

Let ε be the universe of events, $\mathcal{O}$ be the universe of objects, $\mathcal{T}_{obj}$ be the universe of object types, $\mathcal{A}$ be the universe of activities, $\mathcal{C}$ be the universe of attributes, and $\mathcal{V}$ be the universe of attribute values. Let $A \subseteq \mathcal{A}$ be a set of activities and $C \subseteq \mathcal{C}$ be a set of attributes. Each object is mapped to exactly one object type $\pi_{type}: \mathcal{O} \rightarrow \mathcal{T}_{obj}$. An OCEL expressed as $L = (E, O, T_{obj}, \pi_{act}, \pi_{obj}, \pi_{att})$ is composed of four elements:

1) a set of events $E \subseteq \varepsilon$, objects $O \subseteq \mathcal{O}$, and object types $T_{obj} \subseteq \mathcal{T}_{obj}$;

2) a function $\pi_{act}: E \rightarrow A$, mapping events to activities;

3) a function $\pi_{obj}: E \rightarrow O$, mapping events to objects;

4) a function $\pi_{att}: E \times C \rightarrow \mathcal{V}$, mapping events and attributes to attribute values.

Table 1 shows an example of OCEL. A row corresponds to one event, and three essential elements in one event are event ID, activity, and timestamp.

Table 1 Example of OCEL

Event ID	Activity	Timestamp	Order	Item	Payment
e_1	A_{CO}	2021-01-05 09:05	O_1		
e_2	A_{CI}	2021-01-05 14:35		X_1, X_2, Y_1	
e_3	A_{PS}	2021-01-05 17:00	O_1	X_1, X_2, Y_1	1 000

Notes: A_{CO}, A_{CI}, and A_{PS} denote the activities of the creating order, checking item, and packing and shipping, respectively; O_1 denotes the order; X_1, X_2 and Y_1 denote item identifiers representing specific products or materials processed in the workflow.

An event can be associated with three objects of three types: order, item, and payment. For example, an event can be associated with $\pi_{act}(e_3) = \{A_{PS}\}$, $\pi_{att}(e_3) = \{O_1, X_1, X_2, Y_1\}$, and $\pi_{att}(e_3)$ (payment) = 1 000.

Definition 2: OCPN

An OCPN $N_{OCP} = (P, T, F, l, p_t)$ is composed of five elements:

1) a set of places $P = (P_1, P_2, \cdots, P_n)$, which is

finite and is represented by a colored circle;

2) a set of transitions $T = (T_1, T_2, \cdots, T_m)$, which is finite and is represented by a rectangle;

3) a set of directed arcs $F \subseteq (T \times P) \cup (P \times T)$, which is referred to as the flow relation;

4) a label function l: $T \to \mathscr{A}$;

5) a mapping function p_t: $P \to T_{\text{obj}}$, mapping places to object types.

Using the OCEL from Table 1 as an example, its corresponding OCPN can be illustrated, as shown in Fig. 4. Here, *Order* represents the type of order objects, and *Item* represents the type of product objects. Based on the above definitions, the following description can be derived.

1) Places

$$P = \{p_1, p_2, p_3, p_4, p_5, p_6\}.$$

2) Transitions

$$T = \{t_1, t_2, t_3\}.$$

3) Directed arcs

$$F = \{(p_1, t_1), (p_2, t_2), (t_1, p_3), (t_2, p_4), (p_3, t_3), (p_4, t_3), (t_3, p_5), (t_3, p_6)\}.$$

4) Label function

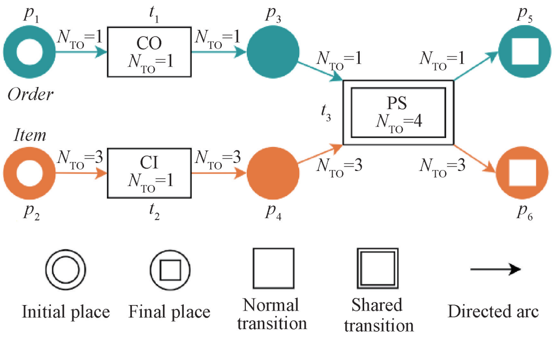
$$l(t_1) = A_{\text{CO}},\ l(t_2) = A_{\text{CI}},\ l(t_3) = A_{\text{PS}}.$$

5) Mapping function

Order type: $p_t(p_1) = p_t(p_3) = p_t(p_5)$;

Item type: $p_t(p_2) = p_t(p_4) = p_t(p_6)$.

The labels of directed arcs and the objects contained within transitions represent the transmission information, denoted by the symbol N_{TO}. For example, $N_{\text{TO}} = 1$ indicates that there is one object passing through this directed arc or that the transition includes one object.



CO—create order; CI—check item; PS—pack and ship.

Fig. 4 Example of corresponding OCPN

2.2 HPM based on OCPN

2.2.1 Definition of HPM

OCPN supplies a broad range of information, addressing problems and providing various viewpoints for follow-up carbon emission analysis. However, OCPN itself lacks the capability for carbon emission analysis, necessitating an extension of its definition. An HPM based on OCPN has been proposed to enhance its utility in carbon emission analysis. The following is the specific definition of the HPM.

Definition 3: HPM

An HPM $M_{\text{HP}} = (P, T, F, p_t, K, W)$ is composed of six elements:

1) a set of events $E \subseteq \mathcal{E}$, objects $O \subseteq \mathcal{O}$, and object types $T_{\text{obj}} \subseteq \mathcal{T}_{\text{obj}}$;

2) a function $\pi_{\text{act}}: E \to A$, mapping events to activities;

3) a function $\pi_{\text{obj}}: E \to O$, mapping events to objects;

4) a function $\pi_{\text{att}}: E \times C \to \mathcal{V}$, mapping events and attributes to attribute values;

5) a function $K: P \to N^+ \cup \{\infty\}$, representing the place capacity, assuming infinite capacity;

6) a flow function $W: F \to N^+$.

2.2.2 HPM mining method

Following the establishment of the HPM's definition, the next critical step is to develop a set of data specifications for the HPM. This provides standardized data requirements for the construction of the HPM. During the construction of the HPM, the integration of more diverse data enhances the model's adaptability and universality. This not only expands the model's data processing capabilities but also effectively addresses the issue of integrating and utilizing diverse data sources within the HPM.

By integrating carbon emission data with process event logs, this study constructs a novel dataset. Subsequently, this event log is converted into OCEL, which enables the use of OCPM to extract OCPN. An example of an HPM dataset is provided, as shown in Table 2.

The columns that contain the most basic information include: event ID, activity, and timestamp. The columns that include object types are: material, energy, product, and the data interface columns. This includes the dynamic data required for object types, for example, in event e_{92} at 2022/6/3 14:29 (timestamp), 9 kg of product 1 (product) was produced through spinning (activity). During the production, 10 kg of fiber (material) and 200 kW·h of electricity (energy) were used. The product yield (data) corresponds to a carbon emission of 3 000 kg CO_2 eq.

The mining method of the HPM is shown in Fig. 5. The procedure begins by determining the type of event log file and analyzing the traditional event log. Subsequently, the event log format is converted and imported as an OCEL file. After that, the OCPM algorithm is applied to generate the HPM.

Table 2 Example of HPM dataset

Event ID	Activity	Material	Energy	Product	Data interface	Timestamp
e_{92}	Spinning	[‘fiber’]	[‘electricity’]	[‘1’]	{ ‘fiber’: ‘10’, ‘electricity’: ‘200’, ‘product’: ‘9’, ‘carbon emission’: ‘3 000’ }	2022/6/3 14:29
e_{93}	Weaving	[‘yarn’]	[‘electricity’]	[‘1’]	{ ‘yarn’: ‘9’, ‘electricity’: ‘400’, ‘product’: ‘8’, ‘carbon emission’: ‘5 000’ }	2022/6/3 11:34
⋮	⋮	⋮	⋮	⋮	⋮	⋮

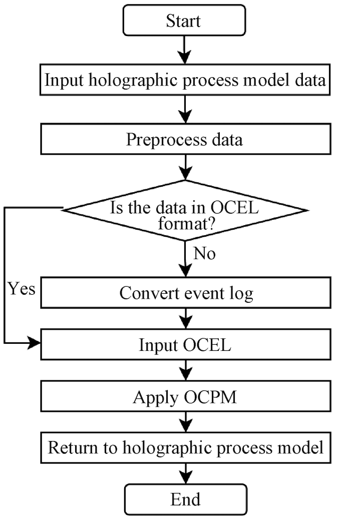


Fig. 5 Flow chart of HPM construction for mining

Guided by the HPM mining methodology, a new HPM has been developed. This model is specifically tailored to the context of current textile manufacturing, as shown in Fig. 6. In the HPM, each place represents a state, with the place in the product type indicating the processing state of the product. The place in the material type represents the inventory and recovery amounts of raw materials, dyes, additives, etc. The place in the energy type represents the capacity and recovery of electrical power. In the HPM, transitions describe a series of actions, where $t_{1,1}-t_{1,6}$ depict material consumption; $t_{1,7}$ and $t_{1,8}$ describe the recovery of materials in the weaving and dyeing stages; $t_{2,1}-t_{2,6}$ describe the technical process of textile manufacturing; $t_{3,1}$ describes the consumption of energy; $t_{3,2}$ and $t_{3,3}$ describe the recovery of energy.

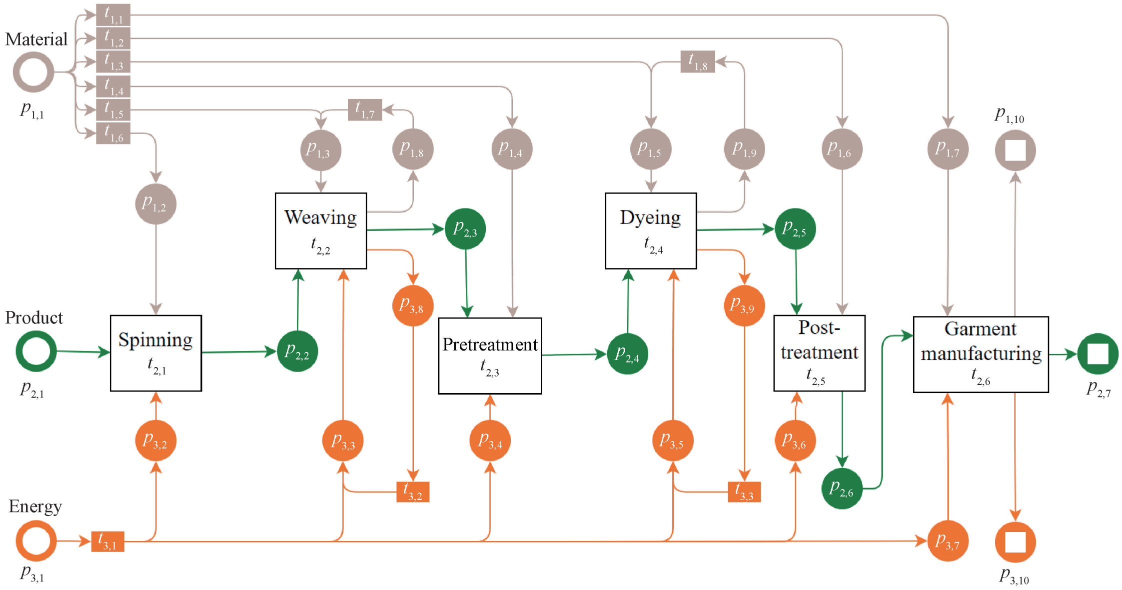


Fig. 6 HPM of textile manufacturing

2.3 Carbon emission analysis

2.3.1 Material and energy consumption

To reduce the complexity of carbon emission calculations while ensuring the reliability of the results, a material with the highest carbon emission among all processes in the textile manufacturing is selected as the primary material, and electricity is chosen as the primary energy source. The carbon emission factors for materials and energy correspond to the respective regions, comply with the standards for carbon emission calculation, and are listed in Table 3.

By multiplying the time in the event log file by the material and energy consumption functions, the daily consumption of materials and energy can be determined. Then, by multiplying the results by the corresponding carbon emission factors, the daily carbon emissions can be calculated. This enables the simulation of the real production conditions of textile manufacturing over the chosen timeframe to simulate carbon emissions, and provides end-to-end results. Subsequently, the simulation results of carbon emissions are utilized for carbon emission analysis. In this setup, the initial places for materials and energy are set to be infinite, with the carbon emissions set to zero. The capacity of each process step's place is infinite.

Table 3 Carbon emission factors for materials and energy across different products

Product type	Material carbon emission factor/ ($kg\ CO_2\ eq/kg$)						Energy carbon emission factor/ ($kg\ CO_2\ eq/kW\cdot h$)
	Fiber	Yarn	Bleaching agent	Dye	Heat-setting agent	Fabric	Electricity
1	0. 120	0. 84	2. 00	5. 0	2. 00	0. 20	0. 81
2	0. 018	0. 35	1. 36	1. 5	2. 95	0. 08	0. 81
3	0. 080	0. 85	2. 00	3. 0	3. 00	0. 18	0. 81

2. 3. 2 Multi-perspective carbon emission analysis

The carbon emission analysis method based on the HPM proposed in this study not only provides a new perspective for carbon emission analysis in the textile manufacturing but also contributes significantly to the green transformation and sustainable development of the industry. The perspectives are as follows.

1) Entire process

The carbon emissions of the entire textile manufacturing process can be visually represented. This provides a means to intuitively display the carbon emissions of the entire production process. This capability facilitates the analysis of carbon emission variations over time. This aspect is referred to as real-time functionality.

$$f_{\text{case}} = \sum_{i=1}^{n} E_i = O_a + O_b + \cdots + O_m, \tag{5}$$

where f_{case} denotes the real-time function; E_i represents the carbon emission in process i; the entire production process consists of n processes; O_a, O_b, $\cdots$, and O_m represent the carbon emissions of different impact factors (a, b, $\cdots$, and m) in the entire production process.

2) Each process

The various factors affecting carbon emissions within process steps can be examined. It allows for the assessment of the influence that various process steps exert on the whole procedure, as shown in Eq. (6).

$$E_1 = O_{1a} + O_{1b} + \cdots + O_{1m}, \tag{6}$$

where E_1 denotes the carbon emission in process 1; O_{1a}, O_{1b}, $\cdots$, and O_{1m} represent the carbon emissions of different impact factors ($1a$, $1b$, $\cdots$, and $1m$) in process 1.

3) Various impact factors

From the perspective of energy consumption of various impact factors, the impact of different types of factors throughout the process can be analyzed. It facilitates the analysis of the effects produced by various factor types over the whole process, as shown in Eq. (7).

$$O_a = \sum_{i=1}^{n} O_{ia}, \tag{7}$$

where O_{ia} represents the carbon emissions of impact factor a in process i; the entire production process consists of n processes.

2. 4 Comparison of carbon emission analysis methods

Our method (HPM) is compared with the traditional methods (LCA and Petri net) in three aspects: data processing types, capabilities, and potential. The comparison results are shown in Table 4.

Table 4 Comparison results of carbon emission analysis methods

Carbon emission analysis method		Data processing type	Capability	Potential
Traditional methods	LCA	Simple	Low	Low
	Petri net	Normal	Medium	Medium
Our method	**HPM**	**Multiple**	**High**	**High**

1) Comparison based on data processing types

The carbon emission analysis methods based on LCA[28-30] only consider the overall carbon emissions of the process, neglecting the information in the process event logs, leading to insufficient data integrity. Although the carbon emission analysis methods based on Petri net[31-32] integrate carbon emission data with process event logs, the data utilized from the event logs during the analysis is limited, making it difficult to derive valuable results. Petri net can integrate carbon emission data with process event logs for data expansion. However, its low extensibility results in a limited range of data types that can be processed. Our method takes into account carbon emission data and the process event logs, ensuring data integrity. Owing to the extensibility of the HPM, it is facile to integrate carbon emission data with process event logs, realizing data sharing and business collaboration, and enhancing the efficiency of carbon emission analysis.

2) Comparison based on processing capabilities

The carbon emission analysis methods based on LCA require separate analysis for each perspective, which can lead to insufficient utilization of actual textile manufacturing process data and overlook many valuable pieces of information. The carbon emission analysis methods based on Petri net use aggregate data to analyze carbon emissions, yielding analysis results with a global perspective but lacking a perception of details. Our method can utilize an HPM to visually represent various types of data and conduct a multi-perspective carbon emission analysis. By integrating carbon emission data with process event logs, a more comprehensive carbon emission analysis can be conducted.

3) Comparison based on the potential for carbon emission reduction

Traditional methods struggle to deeply explore the potential for emission reduction and can only provide general optimization strategies, such as using energy-saving machines and implementing intelligent power management systems. Our method, by comprehensively analyzing the carbon emissions of each process step, aids in identifying potential emission reduction opportunities and can utilize process event logs to propose process optimization strategies for steps with higher carbon emissions.

3 Case Study

Currently, textile manufacturing enterprises are undergoing the process of intelligent transformation, utilizing ERP and MES to record production data. This study selects a certain textile manufacturing enterprise as a case study, which is capable of generating traditional event log files and possesses rich production data. To validate the effectiveness and accuracy of the proposed carbon emission analysis method, we first established an HPM via the OCPM. This HPM was then used to track carbon emissions during the production of pure cotton products and to optimize high-energy-consuming processes across various products.

3.1 Primary parameters configuration

The experiments in this study were conducted in an environment with a PC equipped with an AMD Ryzen 77840H CPU with Radeon 780M Graphics, running at 3.80 GHz, and 32 GB RAM. The holo graphic process model mining method used in the experiments was derived from the open-source libraries PM4PY[33] and OCPA[34].

3.2 HPM mining result

The daily carbon emissions of different pure cotton products in December were simulated by using the HPM, as shown in Fig. 7. It can be observed that the daily carbon emissions of the products exhibit fluctuations. In the first week, product 3 produces the most carbon emissions, while in the subsequent three weeks, product 1 generates the most carbon emissions, and product 2 maintains relatively stable carbon emissions throughout.

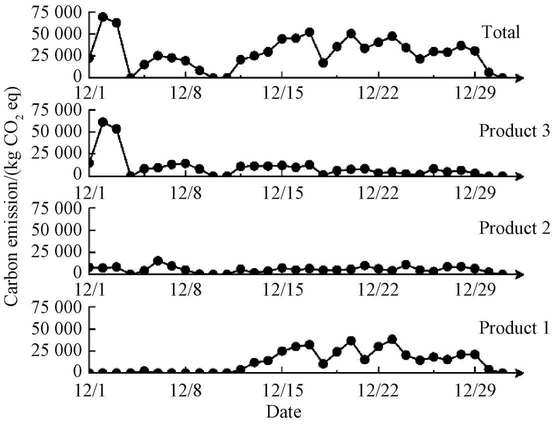


Fig. 7 Daily carbon emissions of different products

By extracting and organizing the data, a complete dataset of the HPM was obtained. Using the OCPM mining tool, the actual textile manufacturing was obtained, as shown in Fig. 8. Different orders share common process nodes, suggesting that these orders involve identical steps and employ the same production equipment. Therefore, special attention should be paid to analyzing such process nodes during process flow design to ensure the reliability and efficiency of the entire production process.

Based on the analysis of Fig. 8, the product flow strictly follows the process flow, while the resource flow does not strictly follow the process flow. For example, there is a loop in the pretreatment process because only the semi-finished products of the current pretreatment process need to be inspected and qualified before dyeing can proceed; otherwise, the process needs to be repeated. Similarly, there is also a loop in the waste flow due to the fact that some waste can be recycled and reused. Furthermore, there are variable arcs within both the resource and waste flows, as the conditions differ for different orders.

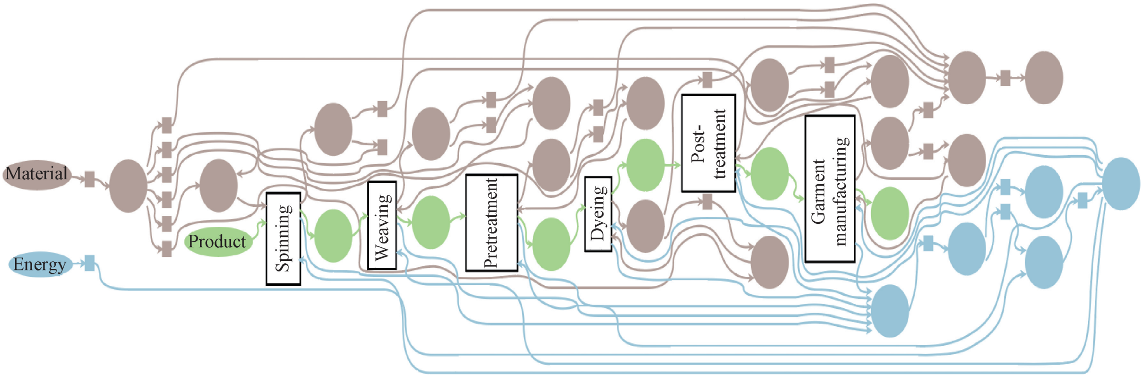


Fig. 8 HPM mining result

3.3 Carbon emission analysis result

3.3.1 Entire process

Product 2 has the lowest carbon footprint of 4.74 kg CO_2 eq/kg, while product 3 has the highest carbon footprint of 8.48 kg CO_2 eq/kg, with the carbon footprint difference between the two nearly doubling, as shown in Fig. 9. Meanwhile, product 1 has a carbon footprint of 7.58 kg CO_2 eq/kg, which is about 0.90 kg CO_2 eq/kg less than that of product 3. By comparing the carbon footprint of product 1 with product 2, it can be concluded that lighter-colored products are more energy-efficient. By comparing product 2 with product 3, it can be concluded that the products produced by using the cloth blank technology are more energy-efficient, primarily because the main technologies involved in cloth blank production are fiber dyeing, carding, drawing, and twisting, which are easier to complete compared to other fabrics.

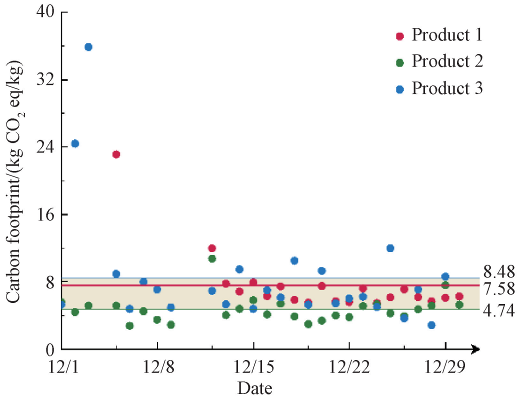


Fig. 9 Carbon footprints of different products

3.3.2 Each process

According to the data in Fig. 10, dyeing is the stage with the highest carbon emission percentage in the production of different types of pure cotton products. This percentage, which varies according to the type of products, accounts for 50%–55% (with an average of 52.15%) of the total carbon emissions. Among various types of textiles, pure cotton products are highly favored by consumers due to their natural and comfortable properties. However, during their production, the dyeing stage becomes the stage with the highest carbon emission percentage. This phenomenon is widely observed in the production of different types of pure cotton products. It should be noted that this percentage can vary depending on the type and specific properties of the pure cotton products.

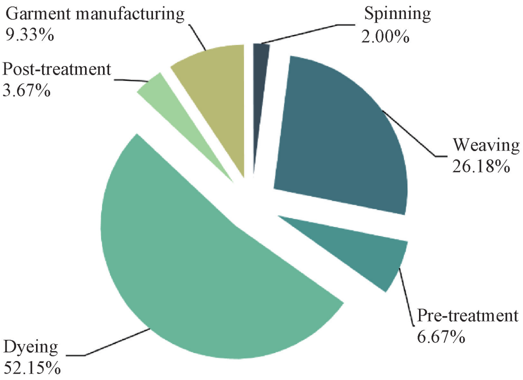


Fig. 10 Average proportion of carbon emissions in different production stages

For pure cotton products, especially those with rich colors and unique designs, the energy consumption ratio in the dyeing stage may approach the upper limit of 55%. This is because the production process requires multiple dyeing and fixing steps to ensure the brightness and durability of the colors. For pure cotton home textiles such as bed sheets and pillowcases, although the colors are relatively simple, the large area means a higher requirement for dyes and auxiliaries, leading to a relatively higher energy consumption ratio in the dyeing stage.

In the production of different types of products, such as clothing, home textiles, and industrial fabrics, the carbon emissions in the dyeing stage mainly originate from several sources. Firstly, the use of dyes and auxiliaries results in significant energy consumption during the production process, as it requires high temperatures and pressures to enable dyes and auxiliaries to fully penetrate the fibers. Secondly, the use of dyeing equipment, such as scouring machines, dyeing machines, and fixation machines, consumes a large amount of electrical and thermal energy during operation. Finally, energy is also required for treating wastewater generated in the dyeing stage.

3.3.3 Various impact factors

Figure 11 shows the carbon emission proportion for different materials and energy during the production process of each product. The electricity consumption contributes the largest proportion of carbon emissions, approximately 50%. Therefore, when optimizing the carbon emissions of pure cotton products, it is crucial to focus on the efficiency of electricity use, such as employing more energy-efficient machines and implementing intelligent power management systems. Whether in the stages of raw material preparation, spinning, weaving, printing and dyeing, or post-treatment, electricity consumption is the primary source of carbon emissions. Therefore, in the pursuit of reducing the overall carbon emissions of pure cotton products, optimizing the efficiency of electricity use has become a critical link.

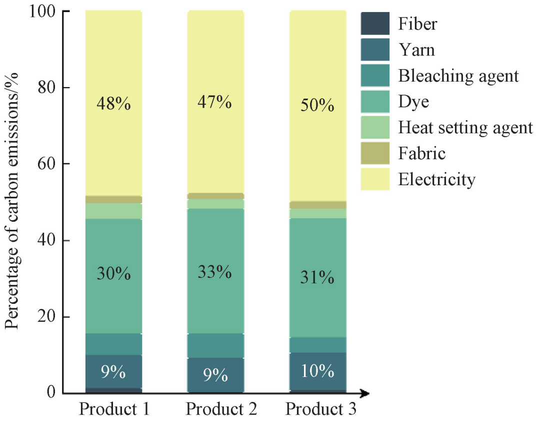


Fig. 11 Proportion of carbon emissions for different materials and energy in each product

3.3.4 Development and execution of optimization strategies

After conducting an accurate carbon emission analysis, a series of targeted clean strategies can be developed. A comparison of the carbon emissions from different products before and after the enterprise implemented process optimization strategies is shown in Fig. 12.

Products 1 and 3 are both dark-colored pure cotton products, with the dyeing process contributing to a significant proportion of carbon emissions, nearly 55%. Implementing a single-step dyeing process for these two products, which decreases the dyeing frequency, results in a 20% reduction in carbon emissions while preserving product quality. Specifically, product 1 shows a reduction of 77 537 kg CO_2 eq in carbon emissions, while product 3 experiences a decrease of 62 724 kg CO_2 eq. Product 2 is a light-colored pure cotton product, and by reducing unnecessary process steps and equipment downtime, the energy efficiency is improved, thereby reducing carbon emissions. Product 2 experiences a decrease in carbon emissions from 172 786 kg CO_2 eq to 155 508 kg CO_2 eq, representing a reduction of approximately 10%.

In actual textile manufacturing, in addition to reducing carbon emissions by optimizing production processes as mentioned above, the following measures can be effectively taken to reduce carbon emissions.

1) Using energy-efficient machinery. By replacing outdated, energy-intensive equipment with advanced energy-saving machines, the power consumption during production can be effectively reduced.

2) Implementing intelligent power management systems. By installing intelligent power management systems, real-time monitoring and optimized scheduling of power consumption during production can be achieved.

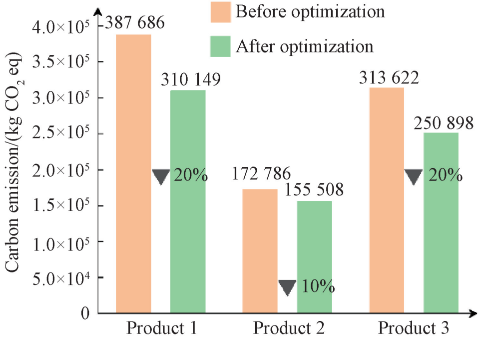


Fig. 12 Comparison results of carbon emissions before and after optimization

3.4 Discussion

This study utilizes a carbon emission analysis method based on an HPM, successfully yielding the following three valuable results.

1) The HPM treats each product as an independent object for tracking, thus enabling the precise analysis and comparison of carbon emission differences among different products throughout the production process. This is challenging to achieve with traditional methods, as traditional methods typically cannot distinguish and track carbon emissions for multiple product lines within the same model.

2) The object-centric characteristic of the HPM enables a direct linkage between carbon emission data and production resources (such as energy and materials). This means that the specific impact of resource usage on carbon emissions can be analyzed, as well as the carbon emission efficiency under different production resource allocation scenarios. Traditional methods, lacking the concept of objects, typically cannot directly represent the complex relationship between resources and carbon emissions.

3) The HPM permits the modeling of parallel operations and interactions within the production process, thereby enabling the analysis of the interactive effects of

carbon emissions among different product lines during parallel production. For instance, when multiple products share certain production resources or stages, the HPM can reveal how different products influence each other's carbon emissions. Traditional methods often struggle to express this parallelism and interaction, thus making it difficult to conduct a precise analysis of this complex dynamic relationship.

4 Conclusions

Owing to the analysis of carbon emissions in the textile manufacturing not considering the importance of process event logs, it is difficult to fully leverage the potential value of this neglected information. In order to solve this problem, this study proposed a carbon emission analysis method based on an HPM. In this method, the system boundary in the textile manufacturing was initially determined, and the characteristics of carbon emissions were analyzed. Subsequently, an HPM based on OCPN was constructed to simulate the textile manufacturing process, and the established HPM was utilized to conduct multi-perspective carbon emission analysis. This method was applied to a textile manufacturing enterprise, and its feasibility was verified by using production data of pure cotton products under three different scenarios.

The results show that the proposed method can fully utilize process event logs and carbon emission data, which aids in conducting a comprehensive carbon emission analysis of textile manufacturing, thereby providing strong support for the green and intelligent transformation of textile manufacturing enterprises. In actual textile manufacturing, in addition to reducing carbon emissions through process optimization, measures such as using energy-efficient machinery and implementing intelligent power management systems can also be adopted.

Many simplifications and hypotheses may increase the uncertainties and limit dynamic representation. Future cases utilizing the proposed carbon emission analysis method could be applied to different products or textile manufacturing processes. Future work will focus on expanding the application scope of the HPM to accommodate a wider variety of textile manufacturing processes.

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基于全息流程模型的纺织生产碳排放分析方法

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摘　要：纺织行业在创造物质财富的同时，也对环境产生了显著影响。特别是纺织生产，作为全生命周期中能源消耗最集中的阶段，其高能耗问题日益突出。然而，目前对纺织生产的碳排放分析侧重于时间动态特性的分析，未能充分考虑物料流转、能源消耗等关键信息。为解决上述问题，该文提出了一种基于全息流程模型的碳排放分析方法。首先，明确了纺织生产过程中的系统边界，并对碳排放特征进行了分析。其次，构建了基于对象为中心 Petri 网的全息流程模型，对纺织生产过程中三种不同场景进行了模拟仿真，并且利用所构建的全息流程模型实现了多种视角的碳排放分析。最后，以某纺织企业的纯棉产品生产数据验证了方法的可行性。结果表明，该方法能够分析出不同因素对纯棉产品生产碳排放的影响，并且通过应用针对性优化策略，碳排放减少了近 20%。该方法有助于推动纺织生产向可持续发展方向迈进。

关键词：纺织生产；碳排放分析；全息流程模型；可持续发展