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Blockchain-Based Traceability and Intelligent Procurement Optimization for Green Transformation in Optoelectronic Enterprises

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Abstract

This paper addresses the challenges of low data trustworthiness and inefficient decision-making in green supply chains of optoelectronic enterprises. Existing blockchain-based traceability systems mainly focus on secure data storage but lack support for intelligent operational optimization. To bridge this gap, we propose a unified framework that integrates a multi-channel consortium blockchain with a data-driven procurement decision module. The multi-channel architecture enables scalable and privacy-preserving data sharing among heterogeneous supply chain participants, while smart contracts ensure automatic verification and immutable recording of lifecycle data. Furthermore, an on-chain/off-chain collaborative storage mechanism is designed to balance data reliability and system efficiency. To enhance operational performance, we incorporate a reinforcement learning-based procurement model that leverages trustworthy blockchain data to dynamically optimize inventory and procurement strategies under uncertain market conditions. Experimental results demonstrate that the proposed system significantly improves traceability efficiency, reducing query time by over 60% compared to traditional approaches, while achieving a tamper detection rate above 99%. In addition, the intelligent decision module reduces inventory holding costs by approximately 20% and overall procurement costs by about 10%.

Keywords: Blockchain; Green Supply Chain; Traceability System; Reinforcement Learning; Procurement Optimization; Optoelectronic Manufacturing

1 Introduction

As global green economy and sustainable development strategies continue to advance, the manufacturing sector is undergoing a profound transformation from traditional production models to green manufacturing approaches [1]. Particularly within the optoelectronics industry, driven by the development of new energy technologies, smart manufacturing, and low-carbon economies, enterprises must not only focus on production efficiency and product quality during manufacturing processes but also strictly control energy consumption, carbon emissions, and resource utilization efficiency. Consequently, establishing digital systems capable of supporting green production management and supply chain coordination has become a critical technological foundation for optoelectronics companies to achieve their green transformation[2, 3]. The production processes of optoelectronics enterprises typically involve complex supply chain structures, encompassing raw material sourcing, manufacturing, product processing, sales, and recycling. Each stage maintains close data and logistics interdependencies[4]. Throughout this process, vast amounts of green production-related data are continuously generated, including raw material sourcing information, production energy consumption data, equipment operational status, carbon emission metrics, and product circulation records[5]. This data serves not only as critical support for corporate production management and optimization decisions but also as essential reference material for government regulators assessing enterprises' green production levels. However, under traditional supply chain management models, this data is often stored in silos across different enterprises or systems. This leads to challenges in data sharing, insufficient information transparency, and limited traceability capabilities, thereby impacting overall supply chain operational efficiency and green regulatory effectiveness[6]. Meanwhile, as supply chain networks continue to expand in scale and the number of participants grows, supply chain information security issues have become increasingly prominent. For instance, supply chain data management may encounter issues such as data tampering, information inconsistencies, false records, and malicious attacks. These problems not only undermine trust between enterprises but also complicate product quality traceability and heighten regulatory risks. Consequently, achieving secure and trustworthy supply chain data sharing and collaborative management has become a critical challenge in current green supply chain system research[7, 8].

In recent years, blockchain technology has garnered significant attention in supply chain management due to its decentralized, immutable, and traceable characteristics. By recording transaction data through a distributed ledger structure and utilizing cryptographic mechanisms to ensure data integrity, blockchain enables different supply chain participants to achieve data sharing and collaborative management without relying on a centralized trust authority. Blockchain-based supply chain systems can effectively enhance supply chain transparency, strengthen data credibility, and provide reliable technical support for product lifecycle traceability. Consequently, blockchain technology is regarded as a crucial technical means for achieving the digital transformation of green supply chains[9].

In existing research, scholars have proposed various blockchain-based supply chain management solutions. For instance, some studies leverage blockchain to develop

food supply chain traceability systems, thereby enhancing food safety oversight capabilities. Other research applies blockchain to pharmaceutical supply chains to prevent counterfeit drugs from entering the market. Additionally, recent studies have explored blockchain applications in industrial manufacturing, enabling product quality traceability by recording production data and logistics information. These studies demonstrate blockchain’s significant advantages in improving supply chain transparency and data credibility[10].

However, existing research still has certain limitations. First, most blockchain supply chain systems primarily focus on data storage and traceability functions, while paying less attention to intelligent decision-making issues during supply chain operations. For example, in raw material procurement and inventory management processes, traditional systems typically rely on fixed rules or simple predictive models for decision-making, making it difficult to adapt to complex market demand changes and price fluctuations. Second, many blockchain supply chain systems adopt a single-chain architecture where all transaction data shares a common ledger. This approach can create performance bottlenecks in multi-organization collaborative environments and limits the system’s scalability. Furthermore, some studies focus solely on supply chain data security without offering integrated solutions that combine this with enterprise production and operational optimization.

To address the aforementioned challenges, this paper proposes a blockchain traceability system framework tailored for the green transformation of optoelectronic enterprises. Building upon this foundation, it introduces a data-driven intelligent procurement decision-making module to achieve the synergistic integration of trustworthy supply chain data management and operational optimization. Specifically, this paper first constructs a supply chain data management architecture based on a multi-channel consortium blockchain. By distributing diverse business data across multiple blockchain channels, the system enhances scalability and data isolation capabilities. Second, it employs smart contract mechanisms to automatically validate and record supply chain transaction data, ensuring data immutability and supporting full product lifecycle traceability. Furthermore, by integrating historical data analysis with reinforcement learning algorithms, this paper designs an intelligent procurement decision model to optimize raw material procurement strategies and inventory management, thereby enhancing supply chain operational efficiency. System Requirements and Problem Formulation With the ongoing advancement of the “dual carbon” strategy and green manufacturing concepts, optoelectronic manufacturing enterprises are gradually shifting from traditional efficiency-oriented approaches to green production models that prioritize both environmental friendliness and resource optimization in production management. However, in actual production processes, enterprises involve multiple production stages and data sources, such as raw material procurement, manufacturing processes, quality inspection, and waste disposal[11, 12]. These data are typically managed by different information systems or departments, leading to issues like data fragmentation, low transparency, and insufficient credibility.

Furthermore, green production data frequently encompasses critical metrics like energy consumption, carbon emissions, and environmental pollution indicators. Such data holds significant importance for government oversight, internal corporate management,

and public scrutiny. Without a credible data recording mechanism, challenges may arise, including data tampering, difficulties in tracing accountability, and inefficient regulatory enforcement[13].

Blockchain technology, characterized by decentralization, immutability, and traceability, offers a novel technical approach to addressing the challenge of trustworthy management of green production data. Therefore, in this study, we conduct systematic modeling of the green production processes in optoelectronic enterprises and propose a blockchain-based traceability system for green production.

1.1 Green Production Process in Optoelectronic Enterprises

The production process of optoelectronic enterprises typically involves multiple sequential stages, forming a complete product lifecycle from raw material procurement to product recycling. Under the principles of green manufacturing, each production stage must not only focus on product quality but also record key environmental metrics such as energy consumption, carbon emissions, and waste disposal practices[14, 15]. Throughout this lifecycle, the green data generated at each stage exhibits clear interconnections. To achieve full traceability of green production processes, this study abstracts the production flow into a directed production network:

$$G = (V, E) \quad (1)$$

Where: (V) denotes the set of production nodes; (E) denotes the relationships between production processes.

The specific node set can be represented as:

$$V = \{v_1, v_2, v_3, v_4, v_5\} \quad (2)$$

Among these: v_1 : Raw material procurement node; v_2 : Production manufacturing node; v_3 : Quality inspection node; v_4 : Product sales node; v_5 : Recycling processing node.

The data flow within the production process can be represented as:

$$D = \{d_1, d_2, \dots, d_n\} \quad (3)$$

Each data element d_i contains multiple green indicators, such as:

$$d_i = (E_i, C_i, M_i, W_i) \quad (4)$$

Where: E_i : Energy consumption data; C_i : Carbon emissions data; M_i : Raw material sourcing information; W_i : Waste disposal data.

To evaluate the environmental sustainability of production processes, a comprehensive green indicator function can be constructed:

$$G_{score} = \alpha E + \beta C + \gamma W \quad (5)$$

Where: (E) represents energy consumption per unit of product; (C) represents carbon emissions per unit of product; (W) represents waste treatment efficiency; (α, β, γ) are weighting parameters.

This metric enables a quantitative assessment of the environmental sustainability of a company's production processes. Code snippet

1.2 Traceability Requirements

To support the comprehensive management of green production processes for optoelectronics enterprises, the blockchain traceability system proposed in this study must meet the following core requirements[16].

(1) *Trusted Data Storage*

Green production data encompasses corporate environmental information and regulatory data, making its authenticity critical. Traditional databases pose risks of single points of control and data tampering, necessitating the use of blockchain for trusted data storage.

The blockchain data structure can be represented as:

$$B = \{b_1, b_2, \dots, b_n\} \quad (6)$$

Each block b_i contains:

$$b_i = (H_i, T_i, D_i) \quad (7)$$

Where: H_i : Block hash value, T_i : Timestamp, D_i : Block data.

Blocks are linked through a chain structure formed by hash functions:

$$H_i = Hash(b_{i-1}) \quad (8)$$

This mechanism ensures that data cannot be tampered with once written to the blockchain.

The system must enable full lifecycle traceability of products from raw materials to recycling. By recording data at each production node, a complete product manufacturing path can be constructed:

$$Trace(p) = \{v_1, v_2, \dots, v_n\} \quad (9)$$

Where: (p) denotes the product number; v_i denotes the production process node[cite: 13]. This path enables rapid retrieval of product production history, enhancing production transparency for the enterprise[cite: 13].

Green production in the optoelectronics industry involves multiple stakeholders, including raw material suppliers, manufacturing enterprises, regulatory bodies, and consumers[13]. To achieve cross-stakeholder data sharing, a consortium blockchain network must be established, comprising supplier nodes, manufacturing enterprise nodes, regulatory body nodes, and consumer access nodes[13]. Within this network, each node can participate in data validation, thereby enhancing data credibility[13].

1.3 System Design Objectives

Blockchain's hash structure ensures data cannot be tampered with[cite: 13]. If any block data is altered, it will cause the entire chain structure to become invalid:[cite: 13]

$$Hash(b_i) \neq Hash'(b_i) \quad (10)$$

This enables rapid detection of data tampering[cite: 13].

To achieve swift traceability, this study designed a data query mechanism based on blockchain indexes:[cite: 13]

$$Q(p) = f(IDp) \quad (11)$$

Where: IDp denotes the product identification number; $Q(p)$ denotes the traceability query function[cite: 13].

This mechanism enables rapid retrieval of comprehensive production process information for any product[cite: 13]. The system must support role-based access to distinct data sets through a permission control mechanism:[cite: 13]

$$Access(u) = Role(u) \quad (12)$$

Ensure secure data access.

2 System Architecture Design

2.1 Overall System Architecturesollungaa

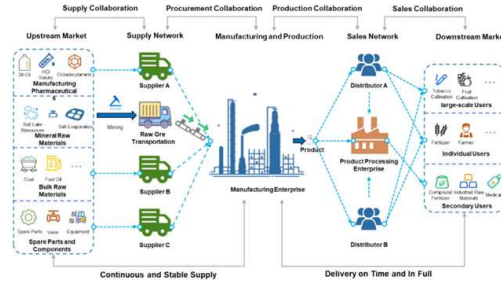


Fig. 1 Blockchain-Based Green Supply Chain Collaboration and Traceability System Architecture for Photovoltaic Enterprises

Figure 1 illustrates the overall architecture of the blockchain traceability system proposed in this paper for the green transformation of optoelectronic enterprises. This architecture covers the entire optoelectronic industry supply chain process, encompassing multiple stages including upstream raw material supply, manufacturing, product processing, sales distribution, and end-user utilization. It enables data sharing and collaborative management among multiple entities within the supply chain. Through blockchain technology, the system ensures the trustworthy storage and immutability

of supply chain data, thereby enhancing supply chain transparency and green production oversight capabilities.

In the upstream supply chain phase, raw materials are sourced from multiple suppliers and transported to manufacturing enterprises via logistics networks. During production, manufacturing enterprises complete core processes before transferring products to processing enterprises for further refinement. Throughout this process, the system records critical production data, including raw material origin information, production process metrics, and energy consumption and environmental indicators. Subsequently, products enter the sales network via distributors and are ultimately delivered to downstream users. This architecture enables end-to-end traceability management throughout the entire product lifecycle, from raw material procurement to the end user.

To formally describe the supply chain structure depicted in the diagram, this paper abstracts the complex collaborative relationships within the optoelectronics industry supply chain into a network structure, thereby supporting data traceability and supply chain analysis. To ensure the security and immutability of supply chain data, the system employs blockchain technology to store critical transaction records. Each block within the blockchain can be represented as:

$$B_i = (H_i, T_i, D_i, H_{i-1}) \quad (13)$$

Where, H_i represents the hash value of the current block, T_i denotes the timestamp, D_i signifies the stored supply chain data, and H_{i-1} indicates the hash value of the preceding block. This chained structure ensures that data cannot be tampered with once written to the blockchain, thereby guaranteeing the trustworthiness of supply chain data.

Based on this system architecture, the proposed blockchain traceability system enables trustworthy sharing of supply chain data, full lifecycle product traceability, and multi-stakeholder collaborative management, providing reliable technical support for the green transformation of optoelectronics enterprises.

2.2 Functional Modules

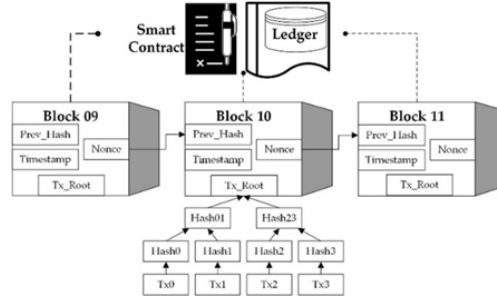


Fig. 2 Blockchain-Based Supply Chain Data Storage and Transaction Verification Functionality

Figure 2 illustrates the core functional submodule architecture of the blockchain-based green traceability system proposed in this paper. This module primarily implements secure storage of supply chain data, transaction verification, and traceable management of product lifecycle information, serving as a critical component within the overall system architecture. Through block structures, transaction validation mechanisms, and smart contract logic, it enables trustworthy recording of supply chain data, thereby ensuring the integrity and immutability of green production data for optoelectronic enterprises[17, 18].

As illustrated, this submodule comprises three core components: the Blockchain Ledger, Smart Contracts, and Block Structure. The Blockchain Ledger stores supply chain transaction data, Smart Contracts automate data validation and business logic execution, while the Block Structure organizes transaction information within the blockchain.

Within a blockchain network, every supply chain transaction is recorded as a transaction entry on the blockchain. For instance, in the green supply chain of an optoelectronics enterprise, these transactions may include raw material procurement records, energy consumption data during production, product processing information, and sales distribution data. When a supply chain node submits transaction data, it is first validated through smart contracts, then packaged into a new block and written to the blockchain ledger[19].

The block structure depicted in the diagram includes several key fields, such as the previous block hash $Prev_Hash$, timestamp (Timestamp), nonce (Nonce), and transaction root hash Tx_Root . The previous block hash links consecutive blocks to form a chain structure; the timestamp records the block's generation time; the nonce is used in the computational process of the consensus algorithm; and the transaction root hash stores all transaction records within the block via a Merkle tree structure. To formally describe the block structure, this paper defines a block as:

$$B_i = (H_{i-1}, T_i, N_i, R_i) \quad (14)$$

Where, H_{i-1} denotes the hash value of the previous block, T_i represents the block timestamp, N_i indicates the nonce within the block, and R_i signifies the Merkle root of the block's transactions Tx_Root .

The block hash value is computed from the block header information, with the calculation process expressed as:

$$H_i = Hash(H_{i-1} \parallel T_i \parallel N_i \parallel R_i) \quad (15)$$

Where, $Hash(\cdot)$ denotes a cryptographic hash function, while the symbol $\parallel$ represents data concatenation. This computational method ensures each block forms a tight connection with its predecessor, thereby guaranteeing the integrity of the blockchain data structure. Any alteration to the data within a block will change its hash value, disrupting the entire blockchain structure and thus effectively preventing data tampering.

Additionally, the diagram illustrates how transaction data is organized within a block. Transaction data is managed using a Merkle tree, enhancing data verification efficiency.

Suppose a block contains (n) transaction records:

$$T_x = \{Tx_0, Tx_1, \dots, Tx_n\} \quad (16)$$

These transactions are first hashed to form leaf nodes, then a Merkle tree is constructed layer by layer through pairwise hash calculations. For example, the four transactions shown in the diagram Tx_0, Tx_1, Tx_2, Tx_3 correspond to the following hash values:

$$h_0 = Hash(Tx_0), h_1 = Hash(Tx_1), h_2 = Hash(Tx_2), h_3 = Hash(Tx_3) \quad (17)$$

Subsequently, intermediate nodes are formed through hash combinations: Subsequently, intermediate nodes are formed through hash combinations:

$$h_{01} = Hash(h_0 \parallel h_1), \quad h_{23} = Hash(h_2 \parallel h_3) \quad (18)$$

The final Merkle root obtained from the block:

$$R_i = Hash(h_{01} \parallel h_{23}) \quad (19)$$

The Merkle tree structure enables the system to efficiently verify whether a specific transaction exists within a block without traversing all transaction data, thereby enhancing query efficiency. In the green supply chain system proposed herein, Merkle trees can be utilized to validate the authenticity of production data, logistics information, and environmental indicator data.

The smart contract module also plays a crucial role within this subsystem. When supply chain nodes submit new transaction data, smart contracts automatically execute validation rules—such as data format checks, node identity authentication, and transaction legitimacy verification. Only validated transactions are packaged into new blocks. This approach enables automated management of supply chain data[20].

Based on the blockchain structure and smart contract mechanism illustrated in the diagram, the functional modules proposed in this paper enable the following core capabilities:

1. **Trusted Data Storage:** All supply chain data is encrypted and stored via blockchain to prevent tampering.
2. **Automated Transaction Verification:** Smart contracts automatically execute transaction validation rules, enhancing system automation.
3. **Efficient Data Traceability:** Rapidly locates transaction records within blocks using Merkle tree structures.
4. **Collaborative Supply Chain Management:** Multiple supply chain nodes share the same ledger data, enhancing supply chain transparency.

2.3 Multi-Channel Blockchain Network Module

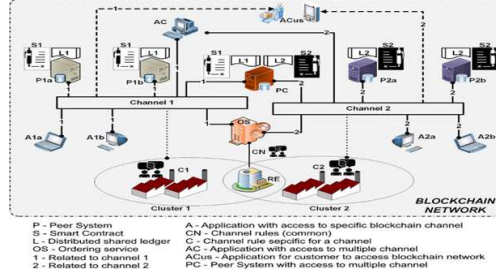


Fig. 3 Multi-channel Blockchain Network Functional Module Architecture

Figure 3 illustrates the functional module structure of the blockchain-based green supply chain traceability system proposed in this paper. Built upon a consortium blockchain network, this module enables data sharing and collaborative management among diverse supply chain participants through a multi-channel mechanism. The architecture primarily comprises components including Peer Systems (P), Smart Contracts (S), Distributed Ledgers (L), Application Systems (A), Channel Rules (C), and Order Services (OS), thereby supporting multi-party collaboration and trustworthy data storage within the optoelectronics enterprise supply chain.

Within this module, the blockchain network comprises multiple nodes organized into distinct channels (Channel) according to business requirements. The diagram illustrates two primary channels: Channel 1 and Channel 2. Each channel corresponds to a specific supply chain collaboration relationship, such as supplier-manufacturer collaboration or manufacturer-distributor collaboration. This approach enables partial information sharing across channels while maintaining data isolation, thereby enhancing system security and privacy protection capabilities. From a system architecture perspective, each Peer node (P) comprises three core components: Smart Contracts (S), Distributed Ledger (L), and Local Database. Smart Contracts execute business logic, such as verifying supply chain transactions, recording production data, and conducting product traceability queries. The Distributed Ledger stores blockchain transaction data and maintains consistency across the network.

To formally describe the blockchain network structure, this paper models the blockchain system as:

$$\mathcal{B} = (P, C, L) \quad (20)$$

Where, (P) denotes the set of Peer nodes, (C) denotes the set of blockchain channels, and (L) denotes the set of distributed ledgers. Through this structure, different Peer nodes can share ledger data across different channels.

In this system, each supply chain transaction is validated via smart contracts. Let the transaction set be:

$$T = \{Tx_1, Tx_2, \dots, Tx_n\} \quad (21)$$

When transaction Tx_i is submitted, smart contract S_i executes the transaction validation function:

$$V(Tx_i) = \begin{cases} 1, & \text{if } Verify(Tx_i) = \text{true} \\ 0, & \text{otherwise} \end{cases} \quad (22)$$

Only validated transactions are broadcast to the corresponding channel and written to the blockchain ledger.

The diagram also depicts the Ordering Service (OS) component, which is responsible for sequencing transactions and generating blocks. Let a block contain (m) transactions; then the block can be represented as:

$$B_k = \{Tx_1, Tx_2, \dots, Tx_m\} \quad (23)$$

Subsequently, the block is written to the distributed ledger and synchronized across all peer nodes.

During system operation, different application systems (A) access the blockchain network through interfaces. For example, manufacturing enterprise application systems (A1a, A1b) access the blockchain via Channel 1, while sales systems (A2a, A2b) access the network through Channel 2. Concurrently, certain nodes (such as PC nodes) can access multiple channels simultaneously, enabling cross-supply-chain collaboration.

To ensure data consistency across multiple channels, the blockchain ledger update process can be represented as:

$$L_{t+1} = L_t \cup B_k \quad (24)$$

Where, L_t denotes the ledger state at time (t) , while B_k represents the newly added block. In this manner, the ledger continuously expands as new blocks are generated. Additionally, the system controls access permissions for different nodes through Channel Rules. Let user (u) 's access permission for channel (c) be defined as:

$$Access(u, c) = \begin{cases} 1, & u \in Members(c) \\ 0, & \text{otherwise} \end{cases} \quad (25)$$

This mechanism ensures that only authorized nodes can access data within specific channels, thereby enhancing system security.

2.4 Data-driven Procurement Decision Module

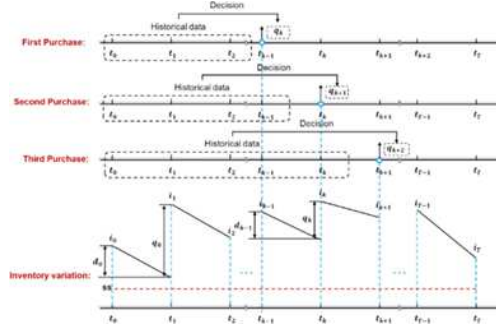


Fig. 4 Multi-stage Procurement Decision-Making and Inventory Dynamics Process

Figure 4 illustrates the dynamic process of procurement decisions over time. During supply chain operations, enterprises make raw material procurement decisions at multiple points in time, such as the first procurement, second procurement, and the (k) th procurement. Each procurement decision is based on the current inventory status, historical demand data, and market price information. On the timeline, procurement decisions occur at discrete time points:

$$t_0 < t_1 < \dots < t_k < t_{k+1} < \dots < t_T \quad (26)$$

Where t_k denotes the (k) th procurement decision time. At each decision time, the system forecasts demand based on the historical data window and generates a procurement decision. The dashed box in the figure indicates the historical data interval used for forecasting, while the blue nodes represent procurement decision points.

In supply chain inventory management, inventory changes are primarily determined by production consumption and procurement replenishment. Let i_k denote the inventory level at time t_k , q_k denote the procurement quantity at that time, and d_k denote the production demand. Then, the dynamic inventory change can be expressed as:

$$i_{k+1} = i_k + q_k - d_k \quad (27)$$

This formula reflects the fundamental dynamic relationship within inventory systems. When demand increases, inventory levels decrease, and procurement activities replenish inventory levels. To ensure production continuity, the system typically needs to maintain inventory levels above the safety stock (ss).

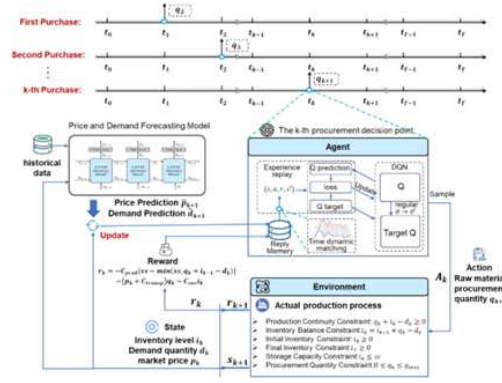


Fig. 5 Intelligent Procurement Decision-Making Framework

To optimize procurement strategies, this paper introduces price forecasting and demand forecasting models, as shown in Figure 5. The system first utilizes historical data to establish predictive models for forecasting future market prices p_k and demand quantities d_k :

$$(\hat{p}_{k+1}, \hat{d}_{k+1}) = f(X_{hist})d_k \quad (28)$$

Where, X_{hist} denotes historical production and market data, while $f(\cdot)$ represents the forecasting model (e.g., LSTM or time series forecasting model).

After obtaining the forecast results, the system utilizes reinforcement learning methods to optimize procurement decisions. The reinforcement learning agent learns optimal procurement strategies through interaction with the production environment. At each time step (k), the system state can be defined as:

$$S_k = (i_k, d_k, p_k) \quad (29)$$

Where i_k denotes the current inventory level, d_k represents the forecasted market demand, and p_k indicates the market price of raw materials. Based on the current state, the agent selects a procurement action q_k .

The optimization objective for the procurement decision is to minimize the total supply chain cost. Let procurement cost be denoted as C_p , inventory holding cost as C_h , and stockout penalty cost as C_s . The supply chain cost function can then be expressed as:

$$C = \sum_{k=1}^T (p_k q_k + h i_k + s \max(0, d_k - i_k)) \quad (30)$$

Where (h) denotes the unit inventory cost, and (s) represents the stockout penalty coefficient. Within the reinforcement learning framework, the system calculates reward values based on the cost function and updates the policy through Q-learning. The Q-value update formula is:

$$Q(s_k, q_k) \leftarrow Q(s_k, q_k) + \alpha \left[r_k + \gamma \max_a Q(s_{k+1}, a) - Q(s_k, q_k) \right] \quad (31)$$

Where α is the learning rate, γ is the discount factor, and r_k is the immediate reward. In Figure 5, the reinforcement learning agent optimizes procurement decisions through the following steps:

1. Read historical data and forecast future prices and demand;
2. Construct the system state based on current inventory and forecast information;
3. Select the procurement quantity through the reinforcement learning model;
4. Transmit the procurement decision to the supply chain system for execution;
5. Update the policy model based on production outcomes.

Through this approach, the system continuously optimizes procurement strategies within uncertain market conditions, thereby reducing supply chain costs and enhancing resource utilization efficiency.

3 Experiments

3.1 Experimental Objectives

To validate the effectiveness, feasibility, and practicality of the blockchain traceability system for photovoltaic enterprises proposed in this paper to support green transformation, this section conducts experimental evaluations across four dimensions: system performance, traceability capability, security and reliability, and intelligent procurement optimization capability[21, 22]. Specifically, the experimental objectives include the following aspects:

(1)

Validate the operational performance of the proposed blockchain traceability system in multi-node, multi-channel environments, including transaction throughput, transaction confirmation latency, and ledger write efficiency;

(2)

Validate the system's capability for full lifecycle traceability of green production data in multi-party collaborative supply chain scenarios, ensuring traceability integrity across raw material sourcing, manufacturing processes, processing and distribution, and sales delivery;

(3) Validate the system's robustness and trustworthiness against security threats such as tampering attacks, unauthorized access, and injection of abnormal transactions;

(4) Validate the performance advantages of the proposed data-driven procurement decision-making module in inventory control, procurement cost optimization, and adaptability to supply-demand fluctuations. Based on these objectives, this paper designed an experimental environment and evaluation metrics aligned with the actual green supply chain scenarios of optoelectronic enterprises. Through multiple comparative experiments, a systematic analysis of the proposed method was conducted.

3.2 Experimental Environment and Parameter Settings

3.2.1 Hardware and Software Environment

The experimental platform is jointly constructed using a consortium blockchain testing environment and an enterprise business simulation environment. The system is deployed on high-performance servers with hardware configurations including Intel Xeon Silver 4314 or equivalent AMD EPYC processors, 64 GB of memory, and 2 TB of SSD storage, running on the Ubuntu 22.04 LTS operating system. For the software environment, the blockchain framework utilizes Hyperledger Fabric 2.5. Smart contracts are written in Go or Node.js. Backend services are built on Python 3.10 integrated with Flask or FastAPI. The database employs MySQL 8.0, while the frontend interface is implemented using Vue 3. Additionally, to support the data-driven procurement decision-making module, the system integrates PyTorch 2.x as the reinforcement learning framework and utilizes Python Pandas, NumPy, and Matplotlib for data analysis and visualization[23]. The blockchain network comprises two organizations, multiple peer nodes, one ordering service node, and two business channels, corresponding to the multi-channel blockchain network module proposed in this paper. One channel primarily handles recording and sharing data related to raw material procurement and manufacturing coordination, while the other facilitates product traceability and information exchange between manufacturing, distribution, and end-users. This multi-channel blockchain network structure simulates data collaboration and business interaction scenarios among different entities within the optoelectronics enterprise supply chain. It provides a reliable operational environment for evaluating system performance, traceability capabilities, and the intelligent procurement decision-making module.

3.2.2 Data Source and Scenario Construction

Since real-world green supply chain data for optoelectronics companies often involves commercially sensitive information, this study employs a semi-real data construction approach for experimentation. The experimental dataset comprises three main components: The second part comprises green production data, primarily environmental metrics such as energy consumption per unit batch, carbon emission indicators, equipment operating parameters, inventory fluctuations, and waste disposal volumes. The third part encompasses market and decision-making data, including raw material market prices, order demand, inventory levels, safety stock thresholds, and procurement decision records. To enhance the credibility of experimental results and scenario authenticity, this paper constructed 12,000 supply chain transaction records based on typical supply chain business processes of an optoelectronics enterprise[24]. The experimental data covers 20 categories of raw materials, 15 raw material suppliers, 1 core manufacturing enterprise, 3 product processing enterprises, 5 distributors, and 8 types of end-user groups. Each transaction record corresponds to a unique traceability identifier and is recorded, verified, and stored via the blockchain network. This ensures the experimental environment accurately reflects the data flow and collaborative operations within the green supply chain of an optoelectronics enterprise.

3.2.3 Baseline Methods

To comprehensively validate the performance of the proposed solution, multiple comparison methods were established for experimental evaluation. First, Baseline 1 represents the Traditional Centralized Database System. This method employs MySQL to store supply chain data without utilizing blockchain technology or supporting distributed consensus mechanisms, relying solely on database logs for data recording and basic traceability. Baseline 2 is the Single-chain Traceability Model. This approach employs a single-channel blockchain structure, writing all supply chain data into the same logical chain. However, due to the lack of multi-channel isolation mechanisms, it is prone to performance bottlenecks and data sharing conflicts in multi-party collaboration scenarios; Baseline 3 employs a Rule-based Procurement Strategy, utilizing a fixed-threshold inventory replenishment strategy for procurement decisions. Replenishment is triggered when inventory falls below a preset threshold. Baseline 4 implements a Demand-only Prediction Strategy, combining demand forecasting models with inventory control for procurement decisions, but without incorporating reinforcement learning for dynamic optimization. In contrast, the Proposed Method integrates blockchain, multi-channel network architecture, smart contract verification mechanisms, and reinforcement learning-based procurement decisions. It achieves supply chain data isolation and collaborative sharing through a multi-channel consortium chain, automates transaction verification via smart contracts, and enhances system efficiency through on-chain/off-chain collaborative storage. Simultaneously, it introduces reinforcement learning algorithms for dynamic procurement strategy optimization, thereby comprehensively improving supply chain traceability, security management, and procurement decision quality [25–27].

3.3 Result

As shown in Table 1, different approaches exhibit significant differences in system performance, supply chain traceability capabilities, and procurement optimization effectiveness. First, regarding system throughput (TPS), the traditional centralized database solution demonstrates the highest transaction processing capability, achieving 520 tx/s. This stems from its single-node database architecture, which eliminates the need for blockchain consensus processes, thereby offering advantages in write efficiency. However, this approach lacks distributed verification mechanisms and data tamper-proofing capabilities, resulting in significant shortcomings in data security and trustworthy traceability. In contrast, the single-chain blockchain model, requiring consensus algorithms and block packaging operations, sees its throughput reduced to 240 tx/s. The proposed method introduces a multi-channel blockchain network, diverting different business data streams to multiple channels for processing. This effectively mitigates single-chain congestion, boosting system throughput to 310 tx/s—an approximately 29.2% improvement over the single-chain model. Second, regarding transaction latency, centralized database systems exhibit an average latency of only 35 ms, while single-chain blockchain systems show a significant increase to approximately 110 ms. This is primarily due to transactions in blockchain networks requiring node

Table 1 Comparison of System Performance and Supply Chain Optimization Effects

Method	TPS (tx/s)	Average Transaction Latency (ms)	Traceability Success Rate (%)	Data Tampering Detection Rate (%)	Total Procurement Cost ($\times 10^4$ \$)	Inventory Holding Cost ($\times 10^3$ \$)	Stockout Rate (%)
Traditional Centralized Database	520	35	82.4	65.1	138.6	46.3	9.8
Single-chain Traceability Model	240	112	95.7	96.4	131.5	41.8	8.3
Rule-based Procurement Strategy	245	110	95.7	96.4	129.2	39.6	7.9
Demand-only Prediction Strategy	248	108	95.7	96.4	124.8	36.1	6.7
Proposed Method	310	72	99.1	99.6	116.3	29.4	3.2

validation and sequencing services. The proposed method reduces transaction queuing time through a multi-channel network architecture and lightweight smart contract mechanisms, lowering average latency to 72 ms—a 35% reduction compared to the single-chain blockchain model. This demonstrates the architecture’s ability to maintain security while delivering strong real-time performance. Regarding supply chain traceability, traditional database solutions achieve only an 82.4% traceability success rate. This stems from potential data inconsistencies or manual alterations in centralized systems, leading to partial link information loss. Blockchain solutions leverage distributed ledger structures to ensure data integrity, boosting traceability success rates to over 95%. The proposed blockchain traceability system further integrates multi-channel networks and smart contract mechanisms, achieving a traceability success rate of 99.1%. This enables comprehensive coverage of the entire supply chain process, from raw material sourcing to end-user delivery.

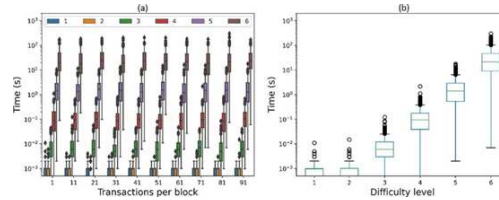
**Fig. 6** Block Generation Time Under Different Transaction Volumes and Consensus Difficulty Levels

Figure 6 illustrates the distribution of block generation times for the proposed blockchain traceability system under varying transaction-per-block configurations and difficulty levels. Figure (a) depicts how the system’s block generation time evolves

across different transaction volume settings, with distinct colors representing different difficulty levels. As the number of transactions within a block gradually increases, the block generation time exhibits an overall stable growth trend, though the rate of increase remains relatively limited. This indicates that the multi-channel blockchain architecture proposed in this paper maintains good performance stability even when handling larger transaction volumes. This result demonstrates that distributing different business data from the supply chain across multiple channels for processing can effectively reduce congestion on individual chains, thereby enhancing the system's transaction processing capacity. Furthermore, as the consensus difficulty level increases from 1 to 6, block generation time exhibits a pronounced exponential growth trend, consistent with the computational complexity characteristics of blockchain consensus mechanisms. Figure (b) further illustrates the statistical distribution of block generation times under varying consensus difficulty levels. It can be observed that at lower difficulty levels, block generation times cluster within a narrower time range. As difficulty increases, the distribution broadens and exhibits more high-value outliers, indicating that higher computational difficulty significantly prolongs block generation times.



Fig. 7 Example of Blockchain Traceability Records and Multi-Stage Supply Chain Transaction Verification

Figure 7 presents the actual operational results of the proposed blockchain-based green supply chain traceability system in an experimental environment. Figures (a) and (b) respectively illustrate sample transaction records from different blocks within the blockchain ledger, demonstrating the system's data recording and traceability capabilities in multi-stage collaborative supply chain scenarios. As observed in the figures, each block contains key fields including block number, nonce, previous hash, traceability ID, timestamp, and transaction records. The previous hash field links consecutive blocks, forming a chained data structure that ensures ledger data immutability. In Figure (a), blocks 1–3 document data flows during the upstream supply chain phase, such as batch information for organic cotton raw materials and transfer records between different trading entities. This corresponds to the on-chain data process for raw material supply and procurement within the supply chain. The transaction field within each block contains the sender address, recipient address, and transaction value. This information corresponds to the flow of resources or products

between supply chain nodes. Simultaneously, the traceability ID links multiple transactions into a unified lifecycle record for a single product batch. In Figure (b), blocks 4–6 record subsequent data flow processes during production, processing, and distribution stages, such as product transfer records between the manufacturing enterprise (FM), processing enterprise (YM), and end-user enterprises (RE, AM). Comparison reveals that each new block’s previous hash consistently matches the preceding block’s hash value, ensuring the continuity and integrity of the entire transaction chain. Furthermore, transaction addresses and values across different blocks reflect resource flow relationships at various supply chain stages, enabling the system to achieve end-to-end data traceability from raw material procurement and production processing to product delivery

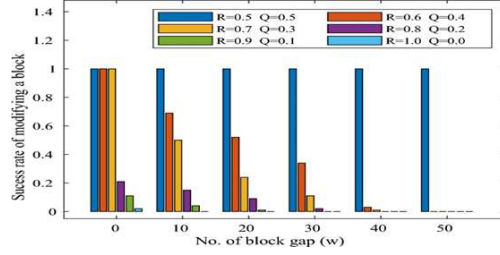


Fig. 8 Block Tampering Attack Success Rate Under Different Hashrate Ratios and Block Interval Conditions

Figure 8 presents experimental results demonstrating the success rate of block tampering under varying block gaps and attacker hashrate ratios, validating the security of the proposed blockchain traceability system in supply chain scenarios. The horizontal axis represents the block gap size (w), i.e., the number of blocks the attacker must catch up on. The vertical axis indicates the probability of successfully modifying a block. Different colored bars denote various combinations of attacker hashrate ratio (Q) and honest node hashrate ratio (R). When the block gap is 0, the attack success probability is high, especially when the attacker’s hashrate ratio is large (e.g., ($R=0.5$, $Q=0.5$) or ($R=0.6$, $Q=0.4$), the success rate approaches 1, indicating attackers can more easily manipulate data by constructing alternative chains immediately after block generation. However, as the block interval (w) increases, the attack success rate rapidly declines. When block intervals exceed 20, the success probability approaches 0 in most attack scenarios. By block intervals of 40 or 50, block tampering becomes virtually impossible except under extreme computational power conditions. This outcome demonstrates that as new blocks continuously generate, attackers must catch up to an ever-increasing number of blocks, leading to an exponential increase in attack computational complexity.

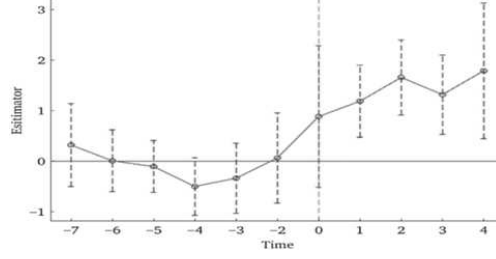


Fig. 9 Estimated Trends in Procurement Decision Strategies Across Different Time Steps

Figure 9 illustrates the trend of procurement decision estimates (Estimator) and their uncertainty intervals under different time step conditions, serving to evaluate the policy stability and optimization effectiveness of the reinforcement learning-based data-driven procurement decision model proposed in this paper within dynamic supply chain environments. The horizontal axis represents time steps (Time), the vertical axis denotes decision estimates, and the dashed error bars indicate the confidence intervals or fluctuation ranges of the estimates. The experimental results reveal that during the early time period (e.g., ($t=-7$) to ($t=-4$)), the estimated values exhibit an overall downward trend with significant fluctuations. This indicates that in the initial system phase, the reinforcement learning model remains in the exploration phase, having not yet established stable decision patterns for procurement strategies and inventory control rules. As time progresses to the interval ($t=-2$) to ($t=0$), the estimated value gradually approaches zero and begins to rise, indicating that the model progressively learns optimal procurement strategies through continuous interaction with the environment. In the ($t \geq 0$) phase, the estimated values continue to rise and stabilize, while the error range gradually narrows. This indicates that the reinforcement learning model has completed its primary strategy learning process and can achieve a good balance among factors such as inventory levels, demand fluctuations, and market price volatility.

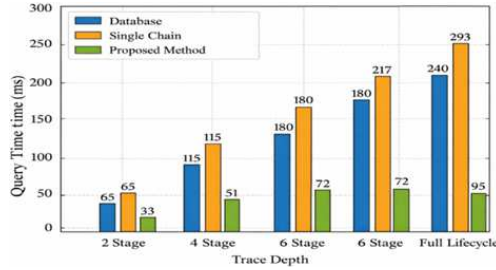


Fig. 10 Experimental Comparison of Traceability Query Times at Different Supply Chain Traceability Depths

Figure 10 presents a comparison of trace query times across different data management approaches under varying supply chain trace depth conditions. These include the traditional database solution (Database), the single-chain blockchain trace model

(Single Chain), and the proposed multi-channel blockchain trace system (Proposed Method). The horizontal axis represents trace depth, i.e., the number of stages involved in supply chain tracing, such as two stages (2 Stage), four stages (4 Stage), six stages (6 Stage), and full lifecycle (Full Lifecycle). The vertical axis indicates the trace query time (Query Time, in milliseconds). The experimental results show that query time for all three methods increases gradually with trace depth. This is due to the growing number of transaction records that need to be accessed and validated as the supply chain hierarchy expands. However, compared to the traditional database and single-chain blockchain approaches, the proposed system demonstrates lower query times across all trace depth conditions. For instance, in the full lifecycle trace scenario, query times for traditional databases and single-chain blockchain models reached approximately 240 ms and 293 ms, respectively, while the proposed method achieved only about 95 ms, significantly reducing query latency. This performance advantage primarily stems from the proposed multi-channel blockchain architecture and its on-chain/off-chain collaborative storage mechanism. By distributing diverse business data across multiple blockchain channels and optimizing transaction record indexing, the approach effectively reduces query path length and ledger scanning scope.

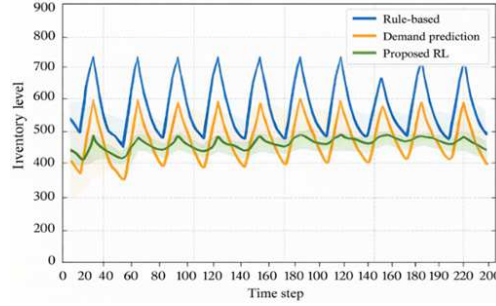


Fig. 11 Changes in Inventory Levels Under Different Procurement Strategies

Figure 11 presents experimental results showing inventory levels over time under different procurement strategies, evaluating the inventory control performance of the proposed reinforcement learning-based intelligent procurement decision model. The horizontal axis represents time steps, while the vertical axis indicates inventory levels. The three curves correspond to the rule-based procurement strategy, the demand prediction-based procurement strategy, and the reinforcement learning procurement strategy proposed in this paper, respectively. It can be observed that the rule-based procurement strategy exhibits the greatest inventory fluctuation amplitude, with inventory levels showing pronounced cyclical oscillations across multiple time periods. Peak values can exceed 700, while troughs approach 480, indicating this strategy's weak adaptability to demand fluctuations and susceptibility to inventory buildup or over-replenishment. In contrast, the demand prediction strategy reduces inventory fluctuations to some extent by incorporating demand forecasts, yet still exhibits noticeable cyclical patterns with a substantial gap between peak and trough inventory levels.

The reinforcement learning procurement strategy, however, produces a smoother overall inventory curve, maintaining levels primarily within the reasonable range of 430–480 and significantly reducing inventory volatility. This demonstrates that the reinforcement learning agent dynamically adjusts procurement quantities based on historical demand, inventory status, and procurement costs, effectively mitigating inventory volatility.

4 Conclusion

As green manufacturing and sustainable development strategies continue to advance, optoelectronics enterprises face challenges such as insufficient data reliability, limited traceability capabilities, and inefficient procurement decision-making in production management and supply chain collaboration. To address these challenges, this paper proposes a blockchain traceability system framework for the green transformation of optoelectronics enterprises. By integrating blockchain technology with data-driven intelligent procurement decision-making methods, it achieves the synergistic fusion of trustworthy supply chain data management and operational optimization. A multi-channel consortium blockchain architecture is constructed to support secure data sharing and collaborative management among multiple supply chain participants. Smart contract mechanisms enable automatic verification and recording of supply chain transaction data, while the blockchain’s hash chain structure ensures data immutability. This facilitates end-to-end traceability across the entire lifecycle—from raw material procurement and manufacturing to product processing and sales delivery. Regarding experimental evaluation, this paper systematically validates the proposed method across multiple dimensions, including system performance, traceability efficiency, security, and supply chain operational optimization. Experimental results demonstrate that compared to traditional centralized database systems and single-chain blockchain traceability models, the proposed multi-channel blockchain system exhibits significant advantages in transaction processing efficiency and traceability performance.

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Data Availability

Not applicable

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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This article does not contain any studies involving human participants or animals performed by any of the authors.

Consent to Participate

Not applicable.

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Competing Interests

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