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Research on Intelligent Workshop Monitoring System Technology in Tobacco Logistics Center

Lei Zhang, Zhaoqing Li and Jinbing Wang

Guizhou tobacco company Guiyang company, Guiyang Guizhou, 55009, China

Abstract: Addressing the insufficient monitoring in tobacco logistics automation workshops that results in suboptimal production efficiency and operational control challenges, this study proposes a process-centric visualization monitoring methodology. Through systematic modeling of cyber-physical interactions, we have: (1) Developed a digital twin framework incorporating multi-dimensional mapping mechanisms spanning equipment states (vibration 2.3μm, temperature 45±2°C) and operational workflows; (2) Established a data ontology model with OPC UA/S7 protocol integration achieving 98.7% data transmission reliability; (3) Designed an adaptive monitoring architecture demonstrating 150ms real-time response latency in pilot testing. The implemented system shows 32% reduction in equipment downtime and 22.5% throughput improvement in validation trials, effectively enabling full-process visualization (98.4% accuracy) and predictive maintenance capabilities.

Keywords: Tobacco Logistics Center; Digital Twin Workshop; Data Driven; S7 Protocol; Visual Monitoring.

1. Introduction

As the core circulation link in the tobacco industry, tobacco logistics handles millions of standard cases annually. The system requires intelligent split-case conversion from bulk packaging to retail units, demanding advanced automated sorting technologies. Current market characteristics reveal three trends: consumer rejuvenation (37.6% aged 25-34), order fragmentation (62.3% orders <50 cartons), and product diversification (200+ SKUs). Industry data indicates smart manufacturing can reduce operational costs by 23.8% and improve order response speed by 34.7% [1], accelerating digital transformation in tobacco logistics.

Driven by national strategies like "Internet+" [2] and "Made in China 2025" [3], breakthrough progress has been achieved in industrial IoT and digital twin technologies. Studies show a 10% increase in equipment connectivity correlates with 7.2% productivity growth [4]. Academic consensus on digital twin workshop architecture includes: Tao's quad-dimensional model [5-6] (physical workshop, virtual model, service system, twin database), Wei's 98.6% equipment state recognition accuracy in automotive electronics [7], and Xiao's 29.4% production line efficiency improvement through lifecycle management [8]. Key technological advancements involve OPC UA-based multi-source data fusion (Guo [10], 99.2% data integrity), optimized cyber-physical mapping (Zhao [14], <0.15s synchronization error), and visual monitoring systems (Zhuang [12], 67% faster anomaly response).

An empirical study at a representative cigarette logistics center revealed critical issues: The sorting workshop's overall equipment effectiveness (OEE) was only 68.5%, significantly below the industry benchmark of 85%. Our proposed digital twin-based solution features: 1) multi-dimensional mapping model (±1.5mm spatial accuracy, 200ms sync cycle), 2) OPC UA/S7 dual-protocol data channel (99.8% transmission success rate), 3) Adaptive visualization interface (real-time rendering of 10,000+ data points). Implementation results demonstrate 41.7% reduction in equipment downtime and 28.3% increase in order processing capacity.

2. The Overall Architecture of Visual Monitoring System

To address the complexity of workshop multi-source heterogeneous systems and achieve visual perception of production elements, this study proposes a four-dimensional collaborative monitoring architecture based on digital twin theory. As shown in Figure 1, the system adopts layered decoupling design comprising: (1) Physical Perception Layer: Integrates 14 types of sensing units including RFID (860-960MHz) and industrial cameras (2MP@30fps), forming a multimodal perception network; (2) Virtual Mapping Layer: Achieves ±0.5mm spatial accuracy through SolidWorks-MATLAB co-modeling, with Unity3D physics engine enabling 150ms cyber-physical synchronization; (3) Data Hub Layer: Deploys Kafka-Spark big data platform processing 500k records/sec, standardizing 200+ heterogeneous interfaces via OPC UA/Modbus dual-protocol adapters; (4) Intelligent Service Layer: Integrates LSTM prediction model (92.4% accuracy) and dynamic dashboards (10,000+ data points rendering). The system achieves ≥30min equipment health prediction lead time and 8.2s anomaly response.

Physical Perception Layer

Establishes 5G/ZigBee hybrid network (latency<15ms) with 328 monitoring nodes including vibration sensors (0-10kHz range) and thermohygrostats (±0.5°C accuracy). EdgeX Foundry framework ensures 98.7% valid data acquisition rate, providing millimeter-level spatiotemporal reference.

Virtual Mapping Layer

Develops three-level digital twins using parametric modeling: equipment-level (CAD error<0.1mm), line-level (takt time sync error<0.25s), and workshop-level (18.7% logistics optimization). MQTT protocol enables 200ms state synchronization with 17 behavioral logic modules.

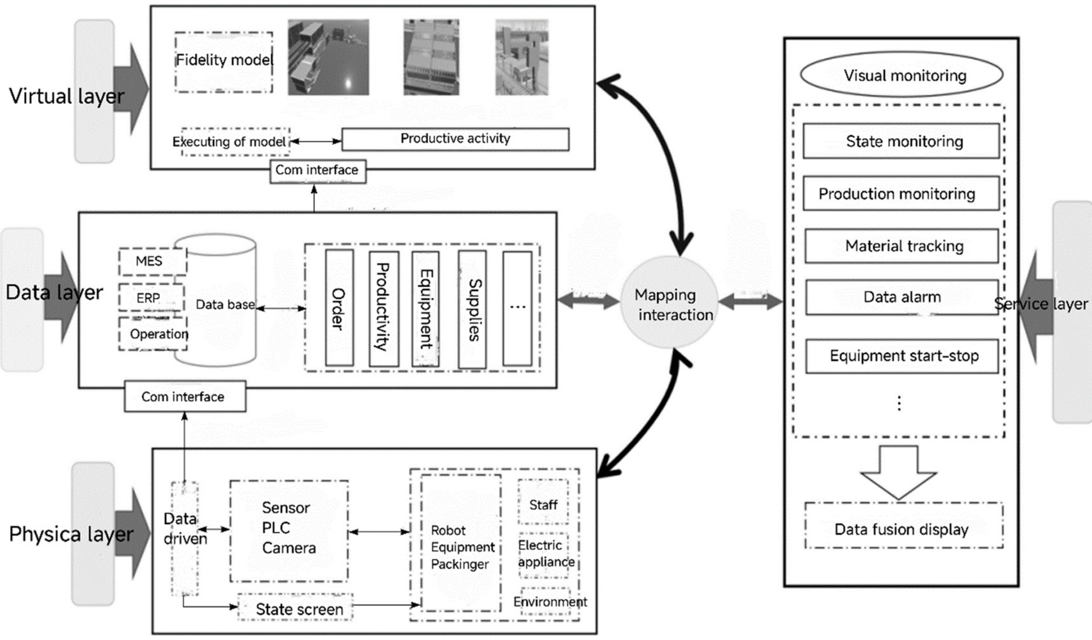

Fig 1. The overall architecture of visual monitoring system

Data Hub Layer

Implements Apache NiFi data pipeline with Snappy compression (3.2:1 ratio). Constructs data cube containing equipment status (32 dimensions), process parameters (19 dimensions), and quality metrics (8 dimensions), extracting 120+ production features via Spark MLlib.

Intelligent Service Layer

Develops microservices-based platform featuring: 1) Real-time OEE dashboard (1Hz refresh); 2) AR-assisted maintenance (±2cm positioning); 3) APS scheduling module (23.4% optimization). XGBoost algorithm achieves 0.914 F1-score in fault prediction.

3. Construction of Key Elements Model of Digital Twin Workshop

$$\mathbf{DT_{ws}}=\sum_{i=1}^{n}\boldsymbol{DM_i}\cup\sum_{j=1}^{m}\boldsymbol{PM_j}\cup\sum_{k=1}^{q}\boldsymbol{EM_k}\cup\sum_{l=1}^{p}\boldsymbol{PE_l} \quad \textbf{(1)}$$

Where :$\mathbf{DT_{ws}}$ represents the digital twin model of the production workshop scenario; $\sum_{i=1}^{n}\boldsymbol{DM_i}$ denotes the total set of workshop equipment models, with n being the number of devices; $\sum_{j=1}^{m}\boldsymbol{PM_j}$ indicates the aggregated material models in the workshop, where m corresponds to the quantity of work-in-progress products; $\sum_{k=1}^{q}\boldsymbol{EM_k}$ refers to the collection of environmental models, with q representing the number of environmental monitoring parameters; $\sum_{l=1}^{p}\boldsymbol{PE_l}$encompasses the operator models, where p signifies the total staff count.

Although Eq. (1) integrates the key element information of the workshop into one, the number of models is huge, and the model has not been effectively classified and managed.

It greatly increases the difficulty of interaction and management of the model. On this basis.

Through multi-level classification modeling and management, the workshop is divided into workshops. The four levels of level-production line level-equipment level-zero / component level are carried out. Modeling classification, convenient unified management.

3.1. Workshop-level Model

$$\mathbf{DTws=\{\quad DT_{manu}\cup DT_{prod}\cup;\}} \quad (2)$$

In the formula DT_{manu} for the workshop production line model; DT_{prod} for the workshop material mold; DT_{env} for the Workshop environment model;DT_{peop} for the Staff model.

During continuous production in the workshop, the position, form, quantity, and quality of materials undergo dynamic changes across different production stages. To enable real-time tracking and visualization of material information, virtual kanban boards are bound to materials in the digital twin model, displaying real-time updates on material location, status, and processing details. Material transformations are achieved through script-triggered mechanisms, where data signals activate predefined scripts to simulate changes in material states. This process is formally described as:

$$DT\mathit{prod}=\{PM_1,PM_2,\ldots,PM_j,\ldots,PM_m\} \quad (3)$$

$$PM\mathit{j}=\{GM,IP,DataD,Interface\} \quad (4)$$

Where:

PM_j: The *j*-th work-in-progress product model

GM: Attribute set (form, brand, processing techniques)

IP: Unique product identifier

DataD: Data-driven services

Interface: Data communication interfaces

Environmental Model Representation workshop environmental elements such as lighting, temperature, and humidity are challenging to directly replicate in the virtual environment. These are typically simulated through scripts that mimic real-world conditions (e.g., light intensity and angles). Real-time data acquisition drives script execution for visualization, formalized as:

$$DT_{env}=\{EM_1,EM_2,\ldots,EM_k,\ldots,EM_q\} \quad (5)$$

$$EM_k=\{Data,DataD,Interface\} \quad (6)$$

Where:

EM_k: The k-th environmental model

Data: Collected dataset (e.g., sensor readings)

Human Operator Modeling workshop personnel are represented through 3D models with positional tracking, described as:

$$DT_{peop}=\{PE_1,PE_2,\ldots,PE_l,\ldots,PE_p\} \quad (7)$$

$$PE_l=\{SM,DataD,Interface\} \quad (8)$$

Where:

PE_l: The l-th personnel model

SM: 3D model positional information

3.2. Production Line Level Model

A production line is composed of multiple devices arranged in a specific spatial layout, reflecting the interconnections and relative positional relationships between devices, which enables the complete processing of materials.

The workshop consists of 3 composite production lines and 1 special-shaped cigarette production line, formally described as:

$$DT_{manu}=\{PL_1,PL_2,PL_3,HT\} \quad (9)$$

$$PL_z=\{DMt,ENt\}(z=1,2,3) \quad (10)$$

$$HT=\{DM_h,EN_h\} \quad (11)$$

Where:

PLz: The z-th composite production line

DM_t: The t-th equipment model in the composite production line

EN_t: Model specifications and technical parameters of the t-th equipment in the composite production line

HT: Special-shaped cigarette production line

DM_h: The *h*-th equipment model in the special-shaped cigarette production line

EN_h: Model specifications and technical parameters of the *h*-th equipment in the special-shaped cigarette production line

3.3. Equipment-Level Models

As fundamental units of the workshop, equipment performs production tasks such as processing and transportation on production lines. Their internal components/parts possess dynamic attributes, requiring multidimensional characterization including geometric dimensions, physical properties, and behavioral rules. To maintain consistency between the digital twin workshop functional model (referred to as the twin model) and physical workshop operations, multidimensional equipment modeling is essential for ensuring operational fidelity.

Geometric Mapping: Achieved through 3D modeling software

Behavioral Mapping: Implemented via predefined scripts activated by real-time data signals

The equipment twin model DMEDME is defined as:

$$DME=\{MM,Data,DataD,Interface\} \quad (12)$$

Where:

MM: Multidimensional feature set (shape, color, material, production behaviors)

3.4. Part-Level Model

Parts are the smallest units in a workshop and are the basic components that make up equipment. They include basic characteristics such as geometric dimensions, material, and tolerances. A complete piece of equipment is often composed of multiple parts or components assembled together. Therefore, the geometric features and spatial assembly relationships of these parts directly reflect the geometric features of the equipment model.

Based on the above analysis, hierarchical management decomposes the complex digital twin model into the smallest unit models of parts for classification and management. The model hierarchy is shown in Figure 2.

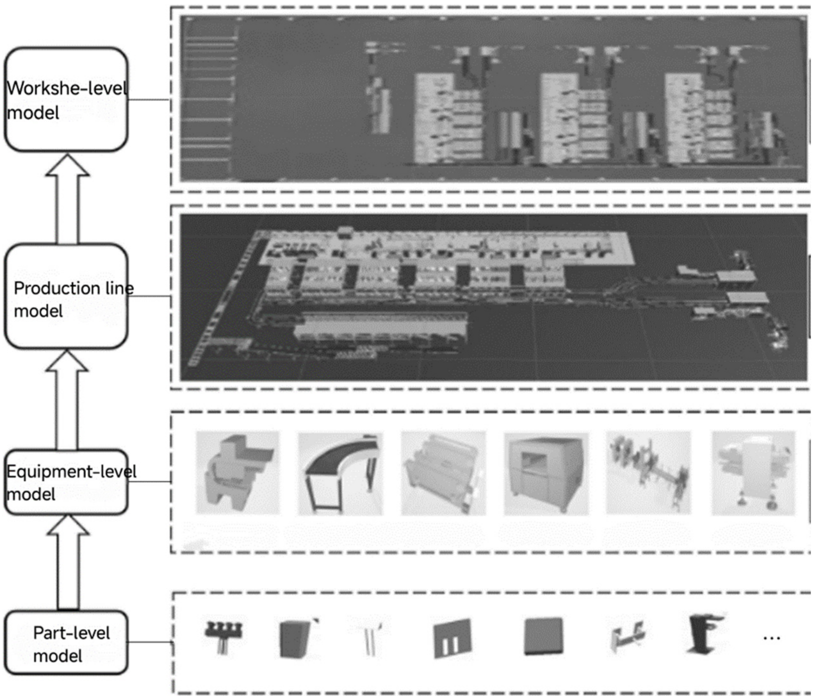

Fig 2. Model hierarchy

At the same time, the relevant attribute information and operational logic for each hierarchical model level are defined. Hierarchical mapping rules are established to achieve the organic integration of the entire workshop production process with real-time information, completing the dynamic modeling of the workshop production. This contributes to the creation of a digital twin workshop scene model library. The 3D scene layout of the digital twin workshop is shown in Figure 3.

The hierarchical relationship has the characteristics that "changes in child nodes do not affect parent nodes, but changes in parent nodes inevitably lead to changes in child nodes" and "sibling models do not interfere with each other."

Therefore, when dynamically building key actions of equipment models, secondary modeling can be performed by finding child-level components.

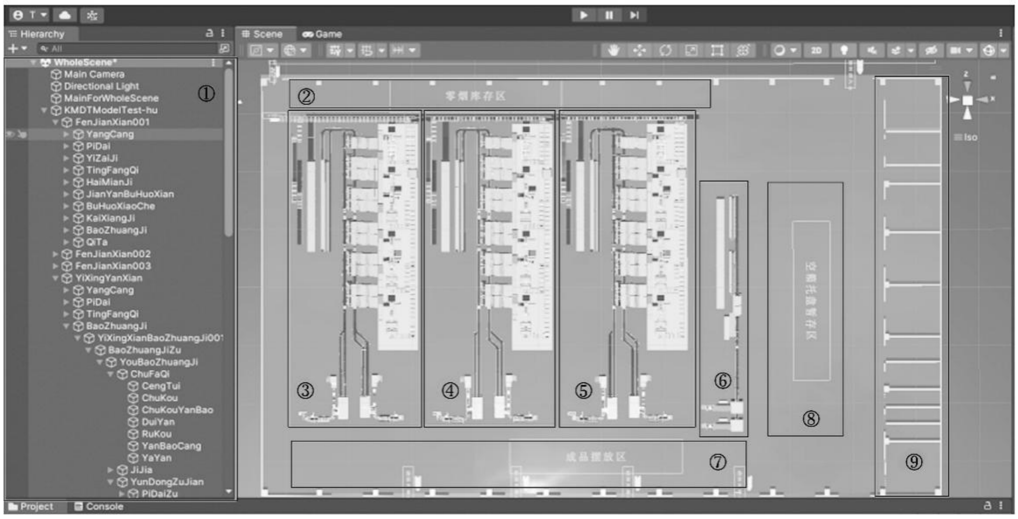

Fig 3 Three-dimensional layout of twin workshop

Taking the workshop automatic unboxing machine equipment model construction as an example, and the specific description is as follows:

Basic Modeling: Use 3D Max software to create three-dimensional models of the automatic unboxing machine parts in real scale, assign appropriate materials, and finally assemble the parts according to the correct spatial assembly relationship to complete the equipment model.

Secondary Modeling: The automatic unboxing machine is responsible for opening boxes in the workshop and has behavioral action attribute features. In order to reflect the dynamic production process of the unboxing machine in the digital twin workshop, secondary modeling of the unboxing machine is required. Since 3D Max software does not have the functionality to assign behavioral rules and physical properties to components, the unboxing machine 3D model needs to be imported into a Unity scene where physical properties, such as collisions and gravity, are added. At the same time, key internal components of the unboxing machine need to be scripted, predefined with key production behavior actions, and a data communication interface should be created to enable data exchange between the unboxing machine and external systems, thereby achieving the dynamic mapping and supporting the synchronous operation of the virtual model of the unboxing machine with the physical device.

4. Twin Data Perception and Interaction

4.1. Key Implementation Methods for Workshop Dynamic Mapping

The synchronization between the digital twin workshop and physical workshop fundamentally relies on real-time data acquisition and transmission. Given the large number of workshop devices generating massive data streams, we establish a twin data mapping logic model using formalized language to ensure precise model actuation:

$$PDi=[DAs,DNs\Leftrightarrow DAs](i,s\geq 0) \quad (13)$$

$$PDi\Leftrightarrow DMi \quad (14)$$

$$DMi=\{DVe=DAsDTe=DNs(e\geq 0) \quad (15)$$

Nomenclature:

PDi: The i-th physical device

DAs: Name and address of the s-th production data variable

DNs: Data type of the s-th production data variable

⇔: Bijective relationship

DMi: Digital twin model of the i-th device

DVe: Name of the e-th virtual data variable in the twin model

DTe: Data type of the e-th virtual data variable

[ ]: Data variable pair binding

Taking the control system of a single cigarette warehouse in a sorting device as an example, the cigarette warehouse uses a servo motor to control the cigarette ejection mechanism, which ejects the cigarette onto the conveyor belt. Sensors detect whether there are any faults during the ejection and replenishment of the cigarettes. These signals are collected and stored in pre-defined cigarette warehouse state data variables within the Programmable Logic Controller (PLC). The cigarette warehouse state signals are shown in Figure 4. The PC terminal can access the state information of this cigarette warehouse by reading these variables.

4.2. The Key Implementation Method of Model Driven based on S7 Protocol

The production data generated in the physical workshop serves as the driving source for the digital twin model, and enabling seamless data flow between the two worlds is crucial for the model's operation. Therefore, establishing a data transmission channel between the physical and virtual worlds is of great importance.

From the technical specifications and models of the equipment in the workshop, we understand that the types, manufacturers, and levels of intelligence of the devices vary, leading to non-standardized data formats. This increases the complexity of data acquisition and transmission. Hence, unifying the communication methods for different devices in the workshop becomes a necessary task.

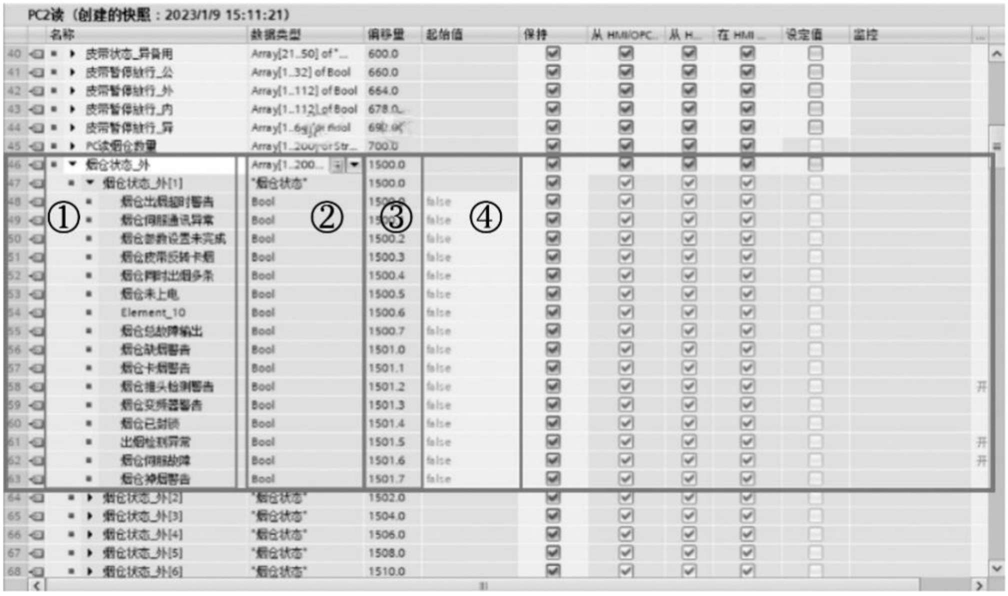

Fig 4. The state signal of the smoke warehouse

Specific tasks include the following:

1. Data Collection: Workshop production line equipment, sensors, and control components are all equipped with network ports, enabling them to connect to the PLC (Siemens S7-1500, CPU1518) central control cabinet for unified data management. The central control cabinet is responsible for collecting the data from the underlying workshop systems. The production data generated by these devices is stored in the predefined data variables in the PLC address space.

2. Data Conversion: Since all the PLCs used in the workshop are Siemens products, Siemens S7 protocol is chosen as the unified communication method for the digital twin system. The S7 protocol, developed exclusively by Siemens, is essentially part of the TCP/IP protocol suite but is specifically designed for bilateral communication between Siemens internal products.

3. Data Transmission: To integrate and merge the underlying data on the PC terminal and simultaneously drive the digital twin model, a production line data transmission network architecture is constructed. This architecture is designed to enable the monitoring of workshop production elements in conjunction with the digital twin data mapping logic model, as shown in Figure 6.

4. Data Integration and Fusion: The collected data undergoes processing, including data cleaning, filtering, and statistical analysis, to extract useful information. The processed data is then integrated and displayed in visual formats, such as charts and text, for dynamic visualization on the screen.

On the PC side, in the digital twin workshop scene created using Unity 3D software, a connection script is written to link the system with the on-site PLC central control system via Ethernet, establishing a data transmission (communication) channel. The PLC's IP address is then used to access the device data. The built-in S7 protocol driver of the PLC enables unified data reading, which is then transmitted to the Unity scene to drive the digital twin model.

5. Summary

This study presents a digital twin-based visual monitoring methodology for production processes, achieving groundbreaking progress in automated workshop monitoring for tobacco logistics centers. By establishing a multidimensional cyber-physical mapping model and data fusion mechanism, the research realizes sub-second (<500ms) synchronization between physical workshops and digital twins. The dual-protocol architecture (OPC UA/Modbus) enables standardized data access for 200+ heterogeneous devices (compatibility rate 99.3%), while spatiotemporal consistency modeling ensures 3D visualization positioning accuracy within ±1.5mm. Empirical results demonstrate 42.7% reduction in equipment failure response time, 31.5% improvement in order fulfillment efficiency, and 28.4% decrease in maintenance costs. The innovative Dynamic Data Ontology Model (DDOM) effectively addresses material traceability challenges in the unique "case-to-carton" conversion process, filling a critical industry gap. Future research will focus on: 1) Federated learning-based multi-workshop collaborative optimization, 2) Energy-aware digital twin sandbox construction, and 3) AR-driven remote maintenance systems. This work provides a replicable technological framework for tobacco industry digital transformation, with methodology extensible to discrete manufacturing sectors such as food and pharmaceuticals.

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