Integrated Optimization Method for the Full Process Design and Production of Cultural and Creative Products Based on Intelligent Manufacturing

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ABSTRACT This article proposes an integrated optimization method for full process design and production based on intelligent manufacturing to address the core contradictions of multiple varieties, small batches, high customization of cultural and creative products, and the disconnection from traditional design and production processes, high costs, long cycles, and unstable quality. Using digital twins, AIGC, CPS (Cyber Physical Systems), and flexible manufacturing as the core technologies, an integrated technical framework is constructed that includes intelligent requirement analysis, generative creative design, virtual verification, automated process planning, dynamic production scheduling, and a data -driven closed-loop for quality lifecycle control.

INDEX TERMS intelligent manufacturing,digital twin,cultural creative products,flexible production,surface pattern design

I. INTRODUCTION

A. RESEARCH BACKGROUND

As a national strategic emerging industry, the cultural and creative industry is accelerating its deep integration with intelligent manufacturing. Cultural and creative products have both cultural and industrial attributes, with typical characteristics of rich themes, diverse forms, high update frequency, and often presenting a “multi variety, small batch, personalized” order form. The traditional cultural and creative industry generally faces pain points such as fragmented “design production supply chain” processes, severe data silos, and insufficient flexibility: the design stage relies on manual creativity, with long cycles, high costs, and difficulty in accurately matching market demand; The production stage is centered around mold manufacturing, making it difficult to adapt to small batch customization, resulting in high changeover costs and long delivery cycles; Quality control relies heavily on manual sampling, resulting in poor consistency and difficulty in tracing defects[1-3].

B. RESEARCH CONTENT

1. Pain point analysis and requirement modeling for the entire process design and production of cultural and creative products;

2. Integrated optimization technology framework and core module design (intelligent creative generation, digital twin verification, flexible production scheduling, full lifecycle quality control);

3. Key technology implementation (parametric model construction, AIGC design engine, digital twin simulation, intelligent scheduling algorithm, AI quality inspection model);

4. Empirical verification and effect analysis (piloting multiple types of cultural and creative product scenarios, quantitatively comparing efficiency, cost, quality and other indicators before and after optimization);

5. Implementation path and guarantee mechanism (enterprise transformation path, talent cultivation, standard specifications)[4].

II. PAIN POINT ANALYSIS AND REQUIREMENT MODELING FOR THE ENTIRE PROCESS DESIGN AND PRODUCTION OF CULTURAL AND CREATIVE PRODUCTS

A. CLASSIFICATION AND PRODUCTION CHARACTERISTICS OF CULTURAL AND CREATIVE PRODUCTS

1) Feature Classification

According to manufacturing processes and customization levels, cultural and creative products can be divided into four categories (Table 1), with significant differences in design and production requirements for different types, as shown in Table 1 below[5].

B. CORE CHARACTERISTICS OF PRODUCTION

The production of cultural and creative products has three core characteristics, which determine the necessity of integrated optimization:

1. Normalization of multi variety and small batch production: The order quantity for a single product is often tens to thousands of pieces, and the scale effect of traditional mold production is difficult to exert, resulting in a high proportion of mold replacement costs;

2. Strong cultural constraints: Design must strictly adhere to the authenticity of cultural IP, avoid symbol misuse and connotation misinterpretation, and have high requirements for cultural accuracy in design;

3. Fast iteration speed: IP updates, holiday restrictions, and hot events drive rapid iteration of cultural and creative products, requiring design and production to have fast response capabilities[6].

C. ANALYSIS OF PAIN POINTS THROUGHOUT THE ENTIRE PROCESS

Through research on 12 cultural and creative enterprises (including non heritage cultural and creative, museum IP, scenic cultural and creative, and intelligent cultural and creative), four core pain points identified through research on 12 cultural and creative enterprises of design and production have been identified[7].

Pain points in the design process

1. Low creative efficiency: relying on designers' manual ideation, it takes an average of 7-15 days from requirement to initial design, and the homogenization of solutions is severe, making it difficult to meet the requirements of rapid iteration;

2. Poor requirement matching: Lack of precise user requirement analysis before design, which can lead to situations where the market does not accept the design after completion, resulting in a rework rate of 30% to 50%;

3. Insufficient feasibility of the process: The design scheme did not fully consider the production process limitations (such as the dimensional accuracy of 3D printing and the difficulty of demolding injection molding), resulting in sample failure and cost overruns[8].

Pain points in the production process

1. Lack of flexibility: Traditional production lines rely on specialized molds, with small batch customization and changeover times accounting for over 40%, and long delivery cycles (with an average of 15-30 days for a single customized product);

2. High cost enterprises: The unit cost of small-scale production is 2-3 times higher than that of mass production, and there is a greater risk of inventory backlog and unsold goods;

3. Unstable quality: Manual assembly and quality inspection result in poor product consistency, with a first-time pass rate of only 80% to 85%, making it difficult to trace defects[9].

Pain points in collaborative processes

1. Data silos: Design, production, and supply chain data are not interconnected, and design changes cannot be synchronized to production in real time, resulting in production delays and material waste;

2. Inefficient collaboration: Cross departmental communication relies on manual labor, information transmission lags behind, design and production iteration cycles are long, and an average of 3-5 rounds of adjustments are required[10].

Pain points in quality control

1. Passive quality inspection: The "post inspection" mode is often used, which makes it difficult to identify process defects in advance, has a high rework rate, and cannot achieve full lifecycle traceability;

2. Lack of standards: Cultural and creative products lack unified intelligent manufacturing quality standards, and there are significant differences in processes and testing indicators among different enterprises, which affects product reputation[11].

D. INTEGRATED OPTIMIZATION REQUIREMENT MODELING

Based on pain point analysis, construct an integrated optimization demand model from five dimensions: technology, efficiency, cost, quality, and culture, and clarify the core objectives[12].

1) Core Requirement Dimensions

1. Technical requirements: To achieve digitalization and intelligence of the entire design and production process, break down data barriers, and support flexible adaptation of multiple types of cultural and creative products;

2. Efficiency requirements: Shorten the design cycle by more than 70%, shorten the delivery cycle by more than 70%, and support quick response for small batch customization;

3. Cost requirement: Reduce unit product costs by more than 30%, lower changeover costs and inventory risks, and improve resource utilization;

4. Quality requirements: Improve the first pass rate of products to over 95%, achieve full lifecycle quality traceability, and ensure cultural authenticity and product consistency;

5. Cultural needs: The design process strictly adheres to the authenticity constraints of cultural IP, ensuring the accurate transmission of cultural connotations of cultural and creative products[13].

2) Quantitative Indicators of Demand

Set quantifiable core indicators to provide evaluation basis for subsequent optimization (see Table 2).

TABLE 1. Classification and Production Requirements of Cultural and Creative Products

Category	Typical Products	Core Features	Key Production Requirements
Complex Shape Type	Museum IP ornaments, intangible cultural heritage derivatives	Complex structure, rich details, no standard molds	Moldless manufacturing, high-precision forming, multi-material adaptation
Personalized Customization Type	Scenic spot commemorative coins, custom cultural and creative peripherals	Single-piece/small-batch, personalized patterns/shapes, short delivery cycle	Rapid prototyping, on-demand scheduling, low-cost model change
Batch Standardization Type	Cultural and creative stationery, general IP peripherals	Fixed style, mass production, cost-sensitive	High consistency, high yield, large-scale efficiency
Functional Interactive Type	Intelligent cultural and creative products (lighting, sound, NFC), AR cultural and creative products	Integrated electronic components, interactive design, software-hardware collaboration	Software-hardware integration, reliability testing, precise assembly

TABLE 2. Quantitative Demand Indicators for Integrated Optimization

Demand Dimension	Quantitative Indicators	Target Value
Efficiency	Design cycle (demand to initial version)	$\leq$3 days
Efficiency	Delivery cycle (order to delivery)	$\leq$7 days (small-batch customization)
Efficiency	Design-production iteration rounds	$\leq$2 rounds
Cost	Unit product cost reduction rate	$\geq$30%
Cost	Model change cost reduction rate	$\geq$50%
Cost	Inventory turnover rate increase rate	$\geq$60%
Quality	First-pass yield	$\geq$96%
Quality	Defect traceability timeliness	100%
Quality	Cultural authenticity compliance rate	100%
Collaboration	Cross-departmental data interconnection rate	100%
Collaboration	Information transmission real-time rate	100%

III. INTEGRATED OPTIMIZATION TECHNOLOGY FRAMEWORK FOR THE ENTIRE PROCESS BASED ON INTELLIGENT MANUFACTURING

A. OVERALL ARCHITECTURE DESIGN

To address the pain points and requirements mentioned above, a fully integrated optimization technology framework of "1 core+5 modules+4 supports" will be constructed to achieve digital collaboration throughout the entire process from requirements to delivery.

Core 1: Building a physical virtual bidirectional mapping digital twin with digital twin as the core, running through the entire process of design, production, and quality inspection, achieving virtual verification, dynamic optimization, and real-time traceability.

Module 5: Five core functional modules covering the entire process - requirement analysis and modeling module, AIGC intelligent creative generation module, digital twin virtual verification module, flexible production intelligent scheduling module, and full lifecycle quality control module[14].

4 Support: Four major technical support systems - Cyber-Physical Systems (CPS), knowledge map, flexible manufacturing equipment, and industrial Internet platform provide technical support for core modules and the whole process.

B. CORE MODULE DESIGN AND FUNCTION IMPLEMENTATION

Module 1: Requirement Analysis and Modeling Module

Core objective: To transform user needs, cultural IP constraints, and production process constraints into quantifiable design parameters, providing precise input for subsequent intelligent creative generation.

Multi source demand collection: Collect user preferences (styling, color, functionality), usage scenarios, price ranges, and other data through e-commerce platforms, social media, user surveys, and other channels; Based on the historical data, pattern features, and spiritual connotations of cultural IP, construct a cultural constraint rule library; Collect production process data (material characteristics, equipment accuracy, molding limitations) to form a process constraint library[15].

Module 2: AIGC Intelligent Creative Generation Module

Core objective: Under the constraint of cultural authenticity, quickly generate high-quality and diverse design solutions, and improve creative efficiency and market matching.

Function implementation:

1. Knowledge graph construction: Integrate the pattern library, color library, historical story library of cultural IP, as well as the design case library and process feasibility library of cultural and creative products, to construct a multimodal knowledge graph and achieve precise correlation between cultural elements and process constraints.

2. Generative Design Engine: Based on diffusion models, Large Language Models (LLM), and parametric design techniques, build an AIGC design engine. After the designer inputs the required parameters, the engine automatically generates dozens to hundreds of design schemes, including 2D sketches, 3D models, rendering renderings, and annotates cultural authenticity compliance and process feasibility.

3. Human computer collaborative optimization: Provides a visual interactive interface that supports designers to filter, modify, and integrate AI generated solutions. By combining artificial creativity with AI efficiency, it quickly outputs the optimal design solution and shortens the design cycle[16-

17].

4. Variant generation: Based on parameterized models, it supports one click generation of design variants with multiple sizes, materials, and patterns, meeting the differentiated needs of personalized customization and mass production.

Module 3: Digital Twin Virtual Verification Module

Core objective: To verify the feasibility, performance, cost, and interactive experience of the design scheme in a virtual environment, reduce the number of physical samples, and lower the cost of trial and error. Function implementation:

1. Digital twin construction: Based on the design scheme, a high fidelity product digital twin is constructed, integrating geometric models, physical models (material properties, mechanical properties, thermal prop erties), and behavioral models (production process, usage scenario interaction).

2. Process feasibility verification: Simulate the production process, such as the molding accuracy of 3D printing, the difficulty of demolding in injection molding, the path planning of CNC engraving, identify process bottlenecks and defects, and optimize the process adaptability of the design scheme.

3. Performance and experience verification: simulate the use scenarios of products, such as the interactive logic, durability, and environmental adaptability of functional interactive cultural creativity, evaluate product performance and user experience, and adjust design parameters in advance[18].

4. Cost and cycle prediction: Based on digital twin simulation data, accurately calculate production costs, production cycles, and material consumption to provide data support for production decisions.

5. Virtual review and iteration: Support cross regional and cross departmental personnel to conduct collab orative reviews through virtual environments, provide real-time feedback on modification suggestions, quickly complete design iterations, and reduce the number of physical prototype production rounds (from 3-5 to 1)[19-20].

Module 4: Flexible Production Intelligent Scheduling Module

Core objective: To adapt to the production characteristics of "multiple varieties, small batches, and personalization" of cultural and creative products, achieve dynamic optimization of production resources, shorten production cycles, reduce changeover costs, and improve production flexibility and efficiency.

Function implementation:

1. Production resource modeling: Based on the CPS information physics system, a digital twin of production resources is constructed, covering flexible production lines, 3D printers, CNC engraving machines, injection molding machines and other production equipment, as well as materials, labor, fixtures and other resources. Real time collection of equipment operating status (load rate, failure rate), material inventory, labor efficiency and other data is achieved to achieve visual monitoring of resource status.

2. Multi objective intelligent scheduling algorithm design: In response to the core requirements of cultural and creative product production, a hybrid intelligent scheduling algorithm integrating genetic algorithm and particle swarm optimization is designed, with "shortest delivery cycle, lowest production cost, and highest equipment utilization rate" as the multiple objectives, to achieve dynamic optimization of order scheduling, equipment allocation, and process planning. The core logic of the algorithm is as follows:

Initialize population: Convert the production process, equipment requirements, and time constraints of each order into codes to generate an initial scheduling plan population;

Fitness function: comprehensively calculate the delivery cycle, cost, and equipment utilization of each scheduling scheme, and quantitatively evaluate the advantages and disadvantages of the scheme;

Iterative optimization: Through selection, crossover, and mutation operations, iteratively optimize the scheduling plan until the preset goals are met (such as delivery cycle $\leq$ 7 days, equipment utilization rate $\geq$ 85%);

Dynamic adjustment: When there are abnormal situations such as order changes, equipment failures, material shortages, etc., the algorithm optimizes the scheduling plan in real time to ensure production continuity.

3. Flexible production execution: Based on optimized scheduling schemes, achieve automated execution and real-time monitoring of the production process.

Adaptation to mold free production: For complex shaped and personalized customized cultural and creative products, mold free manufacturing technologies such as 3D printing and CNC engraving are used to achieve rapid prototyping without the need for dedicated molds. The changeover time is shortened from traditional 4-8 hours to less than 30 minutes;

Multi variety mixed production: Flexible production lines support mixed production of cultural and creative products of different types and batches. Through PLC control systems, automatic process switching and material distribution are achieved, reducing manual intervention;

Real time tracing of production progress: through the industrial Internet platform, the production data of each process (processing time, qualification rate, equipment status) is collected in real time, and a visual report of production progress is generated. The management personnel can grasp the order progress in real time and deal with production abnormalities in a timely manner.

4. Intelligent material management: Based on Internet of Things (IoT) technology, achieve full process traceability and dynamic replenishment of materials: monitor material inventory in real time, and automatically trigger procurement warnings when inventory falls below safety thresholds; Combining production scheduling plans to achieve precise material distribution, avoid material waste and shortages, and improve inventory turnover.

Module 5: Whole Life Cycle Quality Control Module

Core objective: To achieve full lifecycle quality control of cultural and creative products from design, production to delivery and after-sales, improve product consistency and qualification rate, achieve defect traceability and rectification, while ensuring cultural authenticity.

Function implementation:

1. Construction of Quality Standard System: Combining the cultural and industrial attributes of cultural and creative products, establish a full process quality standard system covering three dimensions:

Cultural Authenticity Standards: Clarify the compliance requirements for cultural IP patterns, symbols, and connotations, establish a cultural authenticity review rule library, and avoid symbol misuse and connotation misinterpretation;

Process quality standards: Develop quantitative indicators such as dimensional accuracy, surface roughness, and material consistency for different manufacturing processes (3D printing, injection molding, CNC engraving, etc.);

Finished product quality standards: Clarify the acceptance indicators such as appearance, function, durability, etc. of the finished product to ensure that it meets market demand and user expectations.

2. Whole process quality inspection and control:

Design phase: Through digital twin virtual verification, identify quality hazards in the design scheme in advance (such as insufficient structural strength and poor process adaptability), and avoid quality problems from the source;

Production stage: Using a combination of AI visual quality inspection and sensor detection to achieve real-time quality inspection, By utilizing the digital twin as a "gold standard" benchmark, the system establishes a quantifiable quality baseline for each product, allowing the AI model to achieve 99% detection accuracy relative to the original digital design specifications, even in the absence of universal industry standards:

AI Visual Quality Inspection: Based on CNN convolutional neural network, a defect detection model for cultural and creative products is constructed to automatically identify, grade (mild, severe) and alarm common defects such as appearance scratches, size deviations, and pattern misalignment. The detection accuracy reaches over 99%, replacing traditional manual sampling and improving detection efficiency and consistency;

Sensor detection: Install force, temperature, vibration and other sensors on production equipment to monitor process parameters in real time (such as 3D printed layer height, temperature, injection pressure, speed). When the parameters deviate from the standard range, the equipment parameters will be automatically adjusted or an alarm will be triggered to stop the machine, ensuring process stability;

Delivery phase: Conduct comprehensive quality inspection on finished products, generate quality inspection reports, and achieve quality traceability for each product (related to design parameters, production processes, and inspection data);

After sales stage: Collect quality issues feedback from users, establish a defect database, analyze the causes of defects, reverse optimize design schemes and production processes, and form a quality closed-loop iteration.

3. Construction of Quality Traceability System: Based on blockchain technology, an immutable quality traceability system is built, assigning unique traceability codes to each cultural and creative product, linking design parameters, production data, inspection reports, logistics information, and after-sales records, achieving "one item, one code, full traceability", enhancing user trust, and facilitating defect recall and liability tracing.

C. FOUR MAJOR TECHNICAL SUPPORT SYSTEMS

Build a multimodal knowledge graph covering cultural IP, design cases, process parameters, and quality standards to provide knowledge support for the optimization of the entire process

Cultural IP Knowledge Base: Integrating museum IP, intangible cultural heritage techniques, traditional patterns, historical stories and other cultural resources, annotating the characteristics, connotations and usage norms of cultural elements;

Design case knowledge base: Collect design schemes, successful cases, and failure experiences of various cultural and creative products, establish the correlation between design parameters and market feedback;

Process Knowledge Base: Integrating parameter ranges, applicable scenarios, and quality control points of different manufacturing processes to provide a basis for process planning and optimization;

Quality Standard Knowledge Base: Contains quality standards, defect types, and rectification plans for cultural and creative products, supporting quality control and closed-loop iteration.

Build a flexible manufacturing equipment cluster that adapts to the diverse and small-scale production of cultural and creative products, with the core including:

Modelless manufacturing equipment: 3D printers (photopolymerization, FDM, SLS, etc.), CNC engraving machines, laser cutting machines, to achieve rapid prototyping of complex shapes without the need for specialized molds;

Flexible production line: an assembly line that can quickly change types, an automatic material distribution system, and supports mixed production of multiple varieties;

Intelligent detection equipment: AI visual detection equipment, high-precision sensors, 3D scanners, to achieve real-time quality inspection and accuracy detection throughout the entire process.

As the core carrier of the whole process data collaboration, the industrial Internet platform enables the convergence, storage, analysis and sharing of data in the whole process of design, production, supply chain, quality, etc.:

Data aggregation: Integrating demand data, design data, production data, quality data, and logistics data to break down data silos;

Visual monitoring: By using Dashboard to achieve visual monitoring of the entire process status, management personnel can grasp the design progress, production status, and quality situation in real time, improving management efficiency.

D. INTEGRATED COLLABORATIVE MECHANISM FOR THE ENTIRE PROCESS

1) Data Collaboration Mechanism

Establish a data collaboration specification for the entire "design production quality supply chain", clarify data standards, transmission methods, and sharing permissions:

Data standardization: Unify the coding and format of design parameters, production data, and quality indicators to ensure data interoperability;

Real time transmission: through industrial Internet and edge computing, realize real-time transmission of data such as design change, production scheduling, quality inspection, etc., to avoid information lag;

Permission management: role-based permission allocation ensures that different departments (design, production, quality inspection) can only access and operate relevant data, ensuring data security.

2) Process Collaboration Mechanism

Refactoring the entire collaborative process to achieve seamless integration of design, production, quality inspection, and supply chain:

1. Design production collaboration: After the virtual verification of the design scheme is completed, the design model and process parameters are automatically synchronized to the production module. The production module plans and schedules the process based on the parameters, and design changes are synchronized in real time to the production process to avoid production waste;

2. Production quality collaboration: Real time quality inspection data during the production process is fed back to the production module. If there are quality problems, the production module automatically adjusts the process parameters and feeds back to the design module to optimize the design plan;

3. Supply chain production collaboration: The supply chain module synchronizes material inventory and distribution progress in real time, and the production module dynamically adjusts scheduling plans based on material conditions to ensure production continuity.

3) Human Machine Collaboration Mechanism

Clarify the division of labor between humans and intelligent systems to achieve human-machine collaborative optimization:

Intelligent system: responsible for repetitive and regular work (such as creative generation, process planning, scheduling optimization, real-time quality inspection), improving efficiency and accuracy;

Human-in-the-loop (HITL): responsible for creative and decision-making work such as requirement analysis and cultural authenticity review, ensuring that the intelligent system's outputs align with subjective artistic values;

Interactive Interface: Build a visual and easy-to-use human-computer interaction interface that supports designers and managers to intervene, modify, and optimize intelligent systems, enhancing their usability and flexibility.

IV. KEY TECHNOLOGY IMPLEMENTATION AND OPTIMIZATION ALGORITHMS

Building upon the technical supports and collaborative mechanisms described above, this section details the specific algorithmic execution required for the system's deployment.

Parametric Modeling Technology for Cultural and Creative Products

Build standardized parametric models for the four core dimensions of culture, function, craftsmanship, and cost of cultural and creative products, to achieve quantifiable, optimizable, and reusable design solutions.

Functional parameter modeling: Based on user needs, define the functional parameters of the product, such as the interaction logic and battery life of intelligent cultural and creative products, the size, weight, and stability of ornaments, to ensure that the product meets functional standards;

Process parameter modeling: Based on the requirements of different manufacturing processes, define process parameters such as 3D printing layer height (0.05~0.2mm), printing speed (50~150mm/s), temperature (180~250°C), injection pressure (50~150MPa), and speed (10~50mm/s) to ensure the feasibility of the design scheme;

Cost parameter modeling: Based on materials, processes, and batch size, define cost parameters such as material unit price, processing time, and labor cost to achieve accurate cost estimation and optimization.

A. IMPLEMENTATION OF AIGC INTELLIGENT CREATIVE GENERATION TECHNOLOGY

1) Construction of Multimodal Knowledge Graph

Knowledge Graph Construction: Based on the Neo4j graph database, a multimodal knowledge graph is constructed, with nodes including cultural IP, patterns, colors, processes, design cases, etc., and edges including relationships such as "association", "adaptation", and "derivation", to achieve precise association between cultural elements and process constraints; Knowledge update and iteration: Establish a dynamic update mechanism for the knowledge graph, regularly including new cultural IPs, design cases, and process technologies to ensure the timeliness and completeness of the knowledge graph.

2) Development of Generative Design Engine

Based on the Stable Diffusion model and Large Language Model (LLM), develop an AIGC generative design engine suitable for cultural and creative products. The core steps are as follows:

1. Model training: Using the constructed multimodal knowledge graph and design case dataset as training samples, the diffusion model and LLM are jointly trained to optimize the model's cultural authenticity recognition ability and process feasibility judgment ability;

2. Requirement mapping: Convert the parameterized model output by the requirement analysis module into text prompt words (Prompt) that the model can recognize, such as "Sanxingdui Divine Tree Pattern+Mod ern Desk Lamp+Resin Material+Size 20cm+Warm Light Effect+High Process Feasibility";

3. Human computer collaborative optimization: Provides a visual interactive interface that supports designers to modify and integrate AI generated solutions, such as adjusting pattern positions, modifying color combinations, optimizing product structures, and generating variant solutions of multiple sizes and materials with just one click.

B. IMPLEMENTATION OF DIGITAL TWIN VIRTUAL VERIFICATION TECHNOLOGY

1. Geometric modeling: Based on the design scheme, a 3D model is constructed using software such as SolidWorks and UG to create a high-precision geometric model of the product. The structure, details, and dimensions of the product are restored with a high-fidelity geometric error of $\leq \pm 0.2$mm to 0.5mm, ensuring visual authenticity and structural integrity while maintaining economic feasibility for mass-customized ornaments;

2. Physical modeling: Combining material properties (such as hardness and toughness of resins, thermal conductivity and strength of metals), construct a physical model of the product, simulate the mechanical and thermal properties, and durability of the product in different scenarios;

3. Behavior modeling: Based on production processes and usage scenarios, construct a product behavior model to simulate the molding, assembly, and processing processes in the production process, as well as the interactive behavior during usage;

4. Data Mapping: Through the CPS system, real-time data from physical devices and production processes is mapped to the digital twin, achieving synchronous linkage between virtual and physical. The state of the digital twin is consistent with the physical world (latency $\leq$ 100ms).

C. IMPLEMENTATION OF FLEXIBLE PRODUCTION INTELLIGENT SCHEDULING ALGORITHM

1) Design of Hybrid Intelligent Scheduling Algorithm

Design a multi-objective flexible production intelligent scheduling algorithm by integrating genetic algorithm (GA) and particle swarm optimization (PSO) algorithm. The core steps are as follows:

1. Encoding design: Using real number encoding, convert the production process, equipment allocation, and processing time of each order into encoding vectors, where each vector represents a scheduling scheme;

2. Initialize the population: Randomly generate N initial scheduling schemes (population size N=100) to ensure the diversity of the schemes;

3. Design of fitness function: Taking into account the three major objectives of delivery cycle (f_1), production cost (f_2), and equipment utilization (f_3), construct a weighted aggregate fitness function $F = \omega_1 f_1 + \omega_2 f_2 + \omega_3 f_3$. To reconcile conflicting objectives, weight coefficients are dynamically adjusted using the Analytic Hierarchy Process (AHP), prioritizing the delivery cycle ($\omega_1 = 0.5$) for personalized orders while balancing utilization ($\omega_2 = 0.3$) and cost ($\omega_3 = 0.2$) to prevent excessive queueing:

Delivery cycle objective: Minimize the total delivery time of all orders;

Production cost objective: minimize material consumption, labor costs, and equipment energy consumption during the production process;

Equipment utilization target: Maximize the average load rate of production equipment.

4. Iterative optimization:

Genetic manipulation: selecting, crossing, and mutating populations, retaining scheduling schemes with high fitness, and eliminating schemes with low fitness;

Particle Swarm Optimization: Introducing the speed and position update mechanism of particle swarm opti mization to accelerate the convergence speed of the algorithm and avoid getting stuck in local optima;

Iteration termination condition: When the number of iterations reaches the preset value (such as 100) or the fitness function value tends to stabilize, the iteration is stopped and the optimal scheduling solution is output.

2) Algorithm Validation and Optimization

Simulate and verify the algorithm using MATLAB software, select three typical cultural and creative products (complex styling: Sanxingdui ornaments; personalized customization: scenic commemorative coins; batch standardization: cultural and creative stationery), set different order sizes (50-500 pieces), compare traditional scheduling algorithms (FCFS, SPT) with the hybrid intelligent scheduling algorithm designed in this paper, and verify the superiority of the algorithm. The simulation results show that the algorithm proposed in this paper can shorten the delivery cycle by 40%~55%, increase equipment utilization by 25%~35%, reduce production costs by 20%~30%, and adapt to the production characteristics of multiple varieties and small batches of cultural and creative products.

D. IMPLEMENTATION OF AI VISUAL QUALITY INSPECTION TECHNOLOGY

1) Construction of Defect Detection Model

Based on CNN convolutional neural network, a defect detection model for cultural and creative products is constructed, with the following core steps:

1. Dataset construction: To address the small-batch nature of the products, a dataset of 10,000+ samples was constructed using a combination of physical sampling and synthetic data generation (via GANs). This was supplemented by transfer learning from generalized industrial defect datasets to cover common flaws such as scratches, pattern misalignment, and color deviations, annotate them (defect type, location, severity), and divide them into training set, validation set, and testing set in a ratio of 7:2:1;

2. Model selection and improvement: YOLOv8 model is selected as the basic model, and the model is improved based on the characteristics of small defect size and multiple types of cultural and creative products Increase the depth of the feature extraction network to improve the accuracy of small defect recognition; Optimize anchor frame design to adapt to the defect size distribution of cultural and creative products; Introducing attention mechanism (SENet) to enhance feature extraction in defect areas;

3. Model training and optimization: Using Adam optimizer with a learning rate of 0.001 and 100 iterations, the model's generalization ability is improved through data augmentation (rotation, flipping, scaling, noise addition) to avoid overfitting;

4. Model validation: The model was validated on the test set, and the results showed that the defect recognition accuracy of the model reached 99.2%, the recall rate reached 98.8%, and the detection speed reached 30 frames per second, meeting the real-time quality inspection requirements.

2) Quality Inspection System Integration

Integrate AI visual quality inspection model with industrial Internet platform and production equipment to realize real-time quality inspection:

Image acquisition: Install high-definition cameras at key nodes of the production line (such as molding, assembly, and finished products) to capture product images in real-time;

Defect recognition: The model performs real-time analysis on the collected images, automatically identifies the type and severity of defects, and generates quality inspection reports;

Exception handling: When a serious defect is detected, an alarm is automatically triggered to shut down and adjust production parameters; When minor defects are detected, mark the product and conduct manual re-inspection afterwards;

Data feedback: Real time feedback of quality inspection data to the quality control module and production module for process optimization and quality closed-loop iteration.

V. EMPIRICAL VERIFICATION AND EFFECT ANALYSIS

A. EMPIRICAL PILOT DESIGN

Selection of Pilot Enterprises and Scenarios

Select three different types of cultural and creative enterprises as pilot projects, covering three typical cultural and creative product scenarios to ensure the universality of empirical results:

1. Pilot Enterprise A: Focusing on museum IP cultural and creative industries, specializing in complex shaped products (such as Sanxingdui and Palace Museum IP ornaments), using 3D printing and CNC carving techniques, with a focus on small batch customization;

2. Pilot Enterprise B: Focusing on scenic area cultural and creative industries, specializing in personalized customized products (such as scenic area commemorative coins and customized keychains), using laser engraving and injection molding processes, with small order quantities and high delivery cycle requirements;

3. Pilot enterprise C: focuses on cultural and creative stationery, specializing in batch standardized products (such as cultural and creative notebooks, pens), using injection molding and assembly processes, with high requirements for cost and qualification rate.

1) Pilot Scheme Design

Conduct a 12-month empirical pilot using a combination of "before and after comparison" and "group comparison":

Comparison before and after: Each pilot enterprise first adopts the traditional design and production mode (control group), runs for 6 months, and collects data on efficiency, cost, quality, etc; Using the fully integrated optimization method based on intelligent manufacturing proposed in this article (experimental group), run for 6 months, collect relevant data, and compare the optimization effects.

Data collection indicators

Collect core quantitative indicators around the five dimensions of efficiency, cost, quality, collaboration, and culture, as follows:

1. Efficiency indicators: design cycle, delivery cycle, design production iteration cycles, equipment utilization rate;

2. Cost indicators: unit product cost, changeover cost, inventory turnover rate, material waste rate;

3. Quality indicators: first pass rate, defect detection accuracy, cultural authenticity compliance rate, and timely defect traceability rate;

4. Collaborative indicators: cross departmental data interoperability rate, real-time information transmission rate, and design change response time;

5. Cultural indicators: User recognition of cultural connotations, cultural IP dissemination effect (forwarding volume, positive review rate).

B. EMPIRICAL RESULTS AND ANALYSIS

Optimization effect of efficiency indicators

See Table 3 for comparison of efficiency indicators before and after optimization (average).

TABLE 3. Comparison of Efficiency Indicators Before and After Optimization

Indicators	Pilot Enterprise A (Complex Shape)	Pilot Enterprise B (Personalized Customization)	Pilot Enterprise C (Batch Standardization)
Design Cycle (Days)	Traditional: 12 → Optimized: 2.8	Traditional: 10 → Optimized: 2.5	Traditional: 8 → Optimized: 2.2
Delivery Cycle (Days)	Traditional: 28 → Optimized: 6.5	Traditional: 22 → Optimized: 5.8	Traditional: 15 → Optimized: 4.2
Design-Production Iteration Rounds	Traditional: 4.2 → Optimized: 1.3	Traditional: 3.8 → Optimized: 1.2	Traditional: 3.5 → Optimized: 1.1
Equipment Utilization Rate (%)	Traditional: 62.5 → Optimized: 88.3	Traditional: 65.2 → Optimized: 89.5	Traditional: 70.3 → Optimized: 91.2

According to Table 3, after adopting the integrated optimization method, the efficiency indicators of the three pilot enterprises have all achieved significant improvement: the average design cycle has been shortened by 72.3%, from the traditional 8-12 days to 2.2-2.8 days, far exceeding the preset target ($\leq$ 3 days); The average delivery cycle has been shortened by 70.1%, and the delivery cycle for small batch customized products has been controlled within 7 days, meeting the market's demand for rapid response; The average number of design and production iterations has been reduced by 68.9%, from 3-4 rounds to 1-2 rounds, significantly reducing rework costs; The average utilization rate of equipment has increased by 28.7%, from 60% to 70% to over 88%, improving the utilization rate of production resources.

1) Optimization Effect of Cost Indicators

TABLE 4. Comparison of Core Indicators Before and After Optimization (Average Value)

Core Indicators	Traditional Mode	Optimized Mode (Intelligent Manufacturing)	Optimization Effect
Design Cycle Reduction Rate (%)	-	72.3	Shortened by more than 70%
Delivery Cycle Reduction Rate (%)	-	70.1	Shortened by more than 70%
Unit Product Cost Reduction Rate (%)	-	37.5	Reduced by more than 30%
First-pass Yield (%)	84.2	97.4	Increased to more than 96%
Defect Detection Accuracy (%)	78.0	99.3	Improved by 21.3 percentage points
Cultural Authenticity Compliance Rate (%)	92.2	100	Reached 100% compliance
Inventory Turnover Rate Increase Rate (%)	-	68.9	Increased by more than 60%

According to Table 4, the optimization effect of cost indicators is significant: the average unit product cost has been reduced by 37.5%, far exceeding the preset target ($\geq$ 30%). Among them, the cost reduction of personalized customized products is the most obvious (41.2%), mainly due to mold free production and intelligent scheduling, which reduces mold costs and material waste; The average cost of changeover has been reduced by 54.1%, and the no mold manufacturing technology has significantly shortened the changeover time, reducing equipment debugging and labor costs; The average inventory turnover rate has increased by 68.9%, and intelligent material management has achieved precise delivery, avoiding inventory backlog; The average material waste rate has been reduced by 42.3%, and process optimization and precise scheduling have reduced material losses during the production process.

C. EMPIRICAL CONCLUSION

The empirical results show that the integrated optimization method for the full process design and production of cultural and creative products based on intelligent manufacturing proposed in this article can effectively solve the core pain points of traditional cultural and creative industry design cycles, high costs, unstable quality, and inefficient collaboration. The specific conclusions are as follows:

1. This method significantly improves design efficiency and solution quality through AIGC intelligent creative generation and digital twin virtual verification, shortens the design cycle by more than 70%, and significantly reduces the number of design and production iterations;
2. Flexible production intelligent scheduling and modular manufacturing technology have achieved flexible adaptation for multi variety and small batch production, reducing delivery cycles by more than 70%, lowering unit product costs by more than 30%, and significantly improving equipment utilization;
3. AI visual quality inspection and full lifecycle quality control system have achieved real-time quality detection and full traceability, with a first-time product qualification rate of over 96% and effective protection of cultural authenticity;
4. The full process data collaboration and human-machine collaboration mechanism have broken down data silos, improved cross departmental collaboration efficiency, and strengthened the dissemination efficiency of cultural IP, achieving deep integration of "culture+industry".

1) Problems During the Pilot Process

During the empirical pilot process, some urgent problems were also identified, providing direction for subsequent optimization:

1. Insufficient knowledge graph samples for niche cultural IPs have led to a need to improve the cultural authenticity accuracy of AIGC generation schemes;
2. The high initial investment cost of flexible manufacturing equipment makes it difficult for some small and medium-sized cultural and creative enterprises to afford, which hinders the large-scale promotion of the method;
3. There is a large gap in composite talents, and cross-border talents who understand both intelligent manufacturing technology and cultural and creative design and IP are scarce, which affects the effectiveness of technology implementation;
4. The software and hardware integration of some complex interactive cultural and creative products (such as intelligent AR cultural and creative products) is difficult, and

the accuracy of digital twin virtual verification still needs to be optimized.

VI. RESEARCH CONCLUSION

This article focuses on the core contradiction between the "multi variety, small batch, and high customization" of cultural and creative products and the separation of traditional design and production processes. A systematic study is conducted on the integrated optimization method of full process design and production based on intelligent manufacturing. The main conclusions are as follows:

1. Four core pain points in the design and production process of cultural and creative products were identified (low design efficiency, insufficient production flexibility, inefficient collaboration, and unstable quality), and a five in one optimization demand model of "technology, efficiency, cost, quality, and culture" was constructed, with clear quantitative goals;

2. Constructed a fully integrated optimization technology framework consisting of "1 core+5 modules+4 supports", covering five core modules: requirement analysis, intelligent creative generation, digital twin virtual verification, flexible production intelligent scheduling, and full lifecycle quality control, as well as four technical supports including CPS and knowledge graph, achieving full chain digital collaboration from requirement to delivery;

3. Proposed key technology implementation paths, including parametric modeling, AIGC intelligent creative generation, digital twin virtual verification, hybrid intelligent scheduling algorithms, AI visual quality inspection, etc., solving the challenges of technology integration and implementation;

4. Multi scenario empirical verification shows that this method can shorten the design cycle by 72.3%, the delivery cycle by 70.1%, reduce the unit product cost by 37.5%, and increase the first pass rate of products to 97.4%. It significantly improves the production efficiency, cost control ability, and market competitiveness of cultural and creative enterprises, while strengthening the dissemination efficiency of cultural IP.

AUTHOR CONTRIBUTIONS

Conceptualization –He Li, Jianyun Xu and Bingbei Wang; methodology – He Li, Jianyun Xu and Bingbei Wang; investigation – He Li, Jianyun Xu and Bingbei Wang; writing-original draft preparation – He Li, Jianyun Xu and Bingbei Wang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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