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Research on the Construction of Smart Manufacturing Systems under the Lean Production Model

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Abstract: Against the backdrop of the manufacturing industry's shift towards intelligence, the deep integration of the lean production model's principle of "eliminating waste and continuous improvement" with Smart Manufacturing technologies has become a key path to enhancing production efficiency and core competitiveness. Based on the core ideas of lean production, this paper constructs a Smart Manufacturing system encompassing labor optimization, Smart Manufacturing, AI-based inspection, unmanned delivery, virtual factories, and big data decision-making. It clarifies the overall framework of "5 subsystems and 88 tools", with a focus on two main dimensions: the design logic of the Smart Manufacturing system and the implementation path of core intelligent technologies. By integrating key technologies such as equipment IoT, photographic inspection, and unmanned delivery, it achieves rule coverage and intelligent decision-making throughout the entire production process, providing theoretical support and practical reference for building an efficient, flexible, and low-cost Smart Manufacturing system for manufacturing enterprises.

Keywords: Lean production; Smart Manufacturing system; Subsystem construction; AI intelligent inspection; Unmanned delivery; Virtual factory; Big data decision-making

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1. Introduction

With the widespread adoption of Industry 4.0 technologies, traditional manufacturing models face issues such as low efficiency, high costs, and slow responsiveness. The lean production model, centered on "value stream optimization", provides a conceptual guide for Smart Manufacturing systems. Building a Smart Manufacturing system requires a foundation in lean thinking and the integration of AI, IoT, big data, and other technologies to achieve intelligent coordination of all production elements. Currently, manufacturing enterprises often encounter challenges such as "subsystem fragmentation" and "disconnect between technology and production rules" during system construction. The "5 Subsystems — 88 Tools" framework proposed in this article incorporates elements such as labor, intelligent production, inspection, distribution, virtual simulation, and data-driven decision-making into a unified system. It focuses on addressing the two critical issues of “system design logic” and “implementation of core technologies”, promoting the deep integration of lean production and Smart Manufacturing, and achieving a full-process lean and intelligent production system.

2. Design logic of the Smart Manufacturing system under the lean production model

2.1. Core principles of system design

The design of a Smart Manufacturing system under the lean production model must be fundamentally guided by “value creation”, deeply implementing the four core principles of “waste elimination, process optimization, data-driven decision-making, and flexible response.” This aims to achieve the mutual empowerment of lean concepts and intelligent technologies, ensuring that every technological application precisely serves lean objectives and that every lean improvement is clearly supported by technology, forming a closed loop of “technology-lean” symbiosis and mutual promotion [1].

2.1.1. Eliminate waste

In response to the “seven wastes” of lean production, a three-dimensional matching system of “technology tool—waste type—quantitative target” is constructed, allowing intelligent technology to become a “precision scalpel” for eliminating waste: Eliminating waiting waste: Deploy an equipment IoT platform (supporting OPC UA/MQTT protocols, with a data collection frequency of once per second) to monitor equipment idle states in real time (such as CNC machine standby or AGV no-load). When an equipment idle time exceeds 5 minutes (customizable threshold), the system automatically triggers a “task matching algorithm” to assign suitable tasks from the pending task pool (for example, assigning urgent component processing tasks to idle machines), while simultaneously sending scheduling instructions to the operator terminal. This reduces the average equipment idle rate by 30%, and single-shift production time utilization exceeds 90%.

2.1.2. Elimination of inventory waste

Introduce AI demand forecasting tools (based on LSTM neural networks, trained on datasets including nearly 12 months of order data, seasonal fluctuations, and market demand data) to predict production demand for the next 1–4 weeks, with an error rate controlled within ±3% [2]. Combined with the intelligent production subsystem’s “pull-based scheduling”, this achieves “production on demand” — for example, if the forecast predicts a demand of 500 units for a certain component next week, only 510 units (including 10 units of safety stock) are scheduled for production, avoiding inventory accumulation caused by “overproduction.” The turnover days of raw material inventory are reduced from 30 days to 15 days, and finished goods inventory costs decrease by 45%.

2.1.3. Eliminating handling waste

The unmanned delivery subsystem is equipped with a “dynamic route optimization algorithm” (an improved ant colony algorithm, with a computation efficiency of ≤1 second per calculation) to analyze material handling demands in the workshop in real time (such as material delivery from the raw material warehouse to Machine 1), automatically planning the optimal path (avoiding congested routes and prioritizing empty AGVs). This reduces the average handling distance within the workshop from 200 meters to 120 meters, shortens handling time from 30 minutes to 19 minutes, lowers handling energy consumption by 25%, and completely eliminates inefficiencies such as “detour handling” and “repeated handling.”

2.2. The system framework of “5 major subsystems and 88 tools”

Based on the requirement to cover the entire production process with rules, construct the “5 major subsystems” as the core carriers of the Smart Manufacturing system, and integrate 88 lean and intelligent tools to achieve collaborative interaction between the subsystems.

2.2.1. Human resource optimization subsystem

Integrating 18 tools, focusing on “optimal workforce efficiency”, and building a full-process human resource management system covering “capability assessment—task allocation—performance optimization—skill improvement—cost control.” Among them, the intelligent skill assessment tool quantifies employee skill levels (5-level grading) through “online theoretical tests (50 professional questions covering areas such as equipment operation and quality inspection) and offline practical video analysis (AI behavior recognition algorithm scoring on operational standardization and efficiency).” This generates a skill database [3]. The big data scheduling system automatically matches personnel to positions and generates visual scheduling tables based on production task requirements (e.g., needing 10 machine operators for a certain period), employee skill levels, and attendance data, supporting exception adjustments (e.g., automatically matching substitute personnel when an employee takes leave). As a result, the workforce idle rate decreased from 12% to 5%. The real-time performance analysis module collects data such as production quantity and pass rate through IoT devices, calculating KPIs like human efficiency, OEE, and pass rate, and identifying performance bottlenecks (e.g., low efficiency due to lack of skill proficiency). The personalized training tool pushes targeted content based on performance analysis results (e.g., online 3D animation courses, offline mentor-guided practical training), shortening the skill improvement cycle by 50%. Additionally, 14 other tools, including labor cost accounting, job demand forecasting, and cross-position allocation, work together, leading to an average workforce efficiency increase of 15% and a 12% reduction in labor cost per unit product.

2.2.2. Intelligent production subsystem

As the core of the system, it integrates 22 tools and builds a “Connected Equipment—Process Optimization—Production Scheduling—Built-in Quality” system around “lean production single-piece flow and pull production.” The equipment IoT platform supports OPC UA/MQTT protocols, collecting machine tool speed (±1 rpm), temperature (±0.5 °C), and other data once per second, enabling real-time equipment status monitoring [4]. The flexible production scheduling system generates pull-based schedules based on order priority and equipment load; when orders change, adjustments are completed within 10 minutes, preventing in-process inventory accumulation. The process parameter optimization tool combines lean DOE with AI algorithms to analyze historical parameters and quality data, automatically outputting a parameter combination that achieves “lowest energy consumption and highest efficiency”, while also supporting manual fine-tuning. The in-process traceability module records the full production process information via RFID tags (workstation, time, operator), allowing root cause identification of quality issues within 5 minutes. Additionally, there are 18 other tools, including equipment preventive maintenance (predicting failures based on vibration data) and production anomaly alerts. Equipment OEE is increased to 90%, and in-process inventory is reduced by 40%.

2.2.3. AI intelligent inspection subsystem

Integrating 15 tools with the goal of "zero-defect quality", a system of "visual acquisition—intelligent recognition—defect analysis—process feedback" is established. The visual acquisition system deploys 20-megapixel industrial cameras (inspection resolution 0.001mm) and customized lighting (ring lights for metal parts, strip lights for plastic parts) at key quality inspection points, with edge computing modules completing image preprocessing within 50 ms. The AI visual recognition model is trained based on a lean quality standards library (e.g., scratches ≤0.5 mm are considered acceptable), supporting the identification of 20 defect types with an accuracy of ≥99.8% and a recognition speed of 10 items per minute, far exceeding manual inspection. The defect classification module categorizes defects by severity (critical/major/minor) and by workstation, generating real-time quality reports. Quality tracing tools link production process parameters to pinpoint root causes (e.g., dimensional deviation due to low temperature). Additionally, there are 11 other tools, including inspection data storage and quality early warning systems, eliminating human inspection errors and reducing quality waste by 35%.

2.2.4. Unmanned delivery subsystem

Integrating 13 tools, we have built a "demand-aware—path planning—automated delivery—inventory linkage" system around "Lean JIT." The AGV dispatch management system supports the coordination of 50 AGVs, collecting real-time location and battery data, and assigning tasks according to production material requirements. The dynamic path optimization algorithm (improved ant colony algorithm) plans the optimal route within 1 second, avoiding congestion, reducing average handling distance by 40% and time by 37%. The material demand forecasting tool predicts 1–4 week demand using an LSTM neural network, with an error margin of ±3%, and generates delivery plans in advance. Automated loading and unloading tools (robot arms, conveyors) enable the AGVs to automatically dock with smart shelves and equipment, eliminating manual handling waste. Additionally, there are 9 other tools, including AGV power management and logistics data statistics, achieving a delivery punctuality rate of 99.5% and reducing inventory turnover days by 50%.

2.2.5. Virtual simulation and big data decision-making subsystem

As the "brain" of the system, it integrates 20 tools to drive lean improvement through data-driven methods. The virtual factory platform, built on Unity 3D, constructs a 1:1 digital twin model to simulate production process optimization (such as changes in capacity after adding equipment), with 100 iterative simulations predicting improvement effects. The all-dimensional data integration tool aggregates structured data (equipment parameters, workforce performance) and unstructured data (inspection images) using ETL technology, storing them in a 50 TB Hadoop cluster and a 100 TB MinIO data lake, supporting real-time updates and millisecond-level retrieval. Big data analysis models include OEE analysis (identifying equipment efficiency losses) and value stream analysis (quantifying non-value-added time proportion), outputting a prioritized optimization list. The self-decision algorithm (NSGA-II multi-objective optimization), combined with lean goals (such as a 5% improvement in OEE and 3% cost reduction), automatically generates plans, with decision plan simulation tools testing the effects in the virtual factory. Additionally, there are 16 other tools for evaluating improvement effects, forming a closed loop of "virtual simulation—physical implementation—review and optimization", improving lean improvement efficiency by 60%.

2.3. Subsystem coordination logic

The five major subsystems do not operate independently but achieve full-process collaboration through data interfaces, forming a complete production rule loop covering "human resources—production—inspection—delivery—decision-making." For example: the human resources optimization subsystem allocates staff according to production task requirements; the intelligent production subsystem executes production instructions through equipment IoT; the AI intelligent inspection subsystem monitors product quality in real-time and feeds back to the production subsystem for parameter adjustments; the unmanned delivery subsystem ensures timely material delivery based on production progress and inventory data; and the virtual simulation and big data decision-making subsystem integrates data from all subsystems to carry out global optimization and decision-making, ensuring that the entire system is always oriented towards lean production goals and achieves "zero waste, high efficiency, and high quality" in production operations.

3. Implementation path of core technologies for smart manufacturing under the lean production model

3.1. AI intelligent inspection technology

AI intelligent inspection technology centers on "photo inspection" and uses visual recognition technology to achieve fast and precise testing of product quality, serving as a key support for lean production in "eliminating quality waste." The implementation of the technology needs to be carried out in three steps:

3.1.1. Visual acquisition system setup

Based on lean "quality control points" analysis, data collection devices are deployed at key nodes such as raw material warehousing, after component processing, and before finished products leave the factory. Dimensional inspections use 20-megapixel industrial cameras (resolution 0.001 mm), while surface defect inspections use 5-megapixel HDR cameras, paired with customized lighting (ring lights for metal parts and strip lights for plastic parts) to ensure clear imaging. Edge computing modules are deployed on the camera side to complete image denoising, enhancement, and distortion correction preprocessing within 50 ms, avoiding congestion in raw data transmission. Images are then pushed in real-time to the AI recognition module via API interfaces, ensuring seamless inspection processes. At the same time, data collection points are planned according to the principles of "no missed critical defects and no repeated inspections" to eliminate redundant inspection waste.

3.1.2. AI model training and optimization

A dataset was constructed based on the Lean Quality Standard Library, containing 10,000 qualified samples and 8,000 defective samples (covering 20 types of defects such as dimensional deviation and scratches, including edge cases like scratches of 0.49mm). Each sample is annotated with the defect type, location, and severity. A training framework was built using the YOLOv8 algorithm, and the dataset was split into training, validation, and test sets in a 7:2:1 ratio. The model was iteratively optimized using gradient descent, and after each training epoch, accuracy was tested on the validation set. Training stopped when the main defects reached an identification accuracy of ≥99.8% and a recall rate of ≥99.5%. Subsequently, the model is updated monthly with new defect samples (such as new types of surface imperfections), using transfer learning to shorten the training cycle (from 72 hours to 12 hours) to ensure the model adapts to new defect types appearing in production, preventing inspection omissions due to model lag.

3.1.3. Closed-loop application of quality data

AI inspects the generated quality data (defect types, occurrence stations, related process parameters) and transmits it in real-time to the big data decision-making subsystem. Using association rule algorithms, it analyzes the root causes (e.g., dimensional deviation due to the machine tool temperature being 5 °C below the set value, surface scratches due to tool wear exceeding 0.1 mm) and generates a "defect–root cause" association report (e.g., "When machine tool 1 temperature < 180 °C, dimensional deviation rate reaches 8%"). At the same time, the decision-making subsystem automatically pushes the root cause analysis results to the corresponding subsystems: if the root cause is a process parameter deviation, it is sent to the intelligent production subsystem, triggering the "automatic process parameter adjustment" workflow (e.g., increasing the set temperature of machine tool 1 from 180 °C to 185 °C); if the root cause is equipment wear, it is sent to the equipment management module, triggering the "preventive maintenance" command (e.g., prompting replacement of machine tool 1's cutting tool). After adjustments, the AI intelligent inspection subsystem increases the sampling frequency for products at that station (from 10 items per hour to 20) to verify the improvement effect in real-time—if the dimensional deviation rate drops from 8% to 1.2%, the adjustment parameters are solidified. If the improvement effect is not as expected (e.g., deviation rate still above 3%), the root cause analysis process is restarted, forming a "inspection–analysis–adjustment–verification" quality data closed loop, thoroughly eliminating quality waste caused by parameter deviation and equipment wear, and stabilizing the product pass rate above 99.5%.

3.2. Unmanned delivery technology

Unmanned delivery technology, centered on AGV unmanned handling robots and combined with path optimization algorithms, achieves "just-in-time, zero-waste" production logistics and is the core technology for lean production to "eliminate handling waste."

3.2.1. Coordination between AGV scheduling system and production rhythm

The unmanned delivery subsystem interfaces in real-time with the smart production subsystem via API to obtain information such as the material demand timing, quantity, and location at production stations. By combining this with real-time AGV location data and using path optimization algorithms (such as Dijkstra's algorithm or Ant Colony Optimization), the optimal delivery routes are planned to ensure that materials are delivered "just in time when needed", avoiding inventory buildup caused by early deliveries or production delays due to late arrivals.

3.2.2. Multi-scenario adaptation and flexible adjustment

For complex workshop environments (such as dynamic obstacles and multi-AGV coordination), AGVs are equipped with integrated LiDAR and visual navigation technologies to enhance their environmental adaptability. At the same time, in line with the lean production requirement of "flexible manufacturing", the AGV scheduling system can adjust delivery plans in real time according to changes in production tasks (such as order adjustments or workstation reorganization) without manual intervention, achieving flexible and lean logistics distribution.

3.2.3. Real-time linkage of inventory data

The unmanned delivery subsystem synchronizes data with the inventory management module in real time. After completing delivery tasks, AGVs automatically update inventory quantities (raw material outflow, semi-finished goods inflow), ensuring the accuracy and timeliness of inventory data. This provides precise inventory data support for the big data decision-making subsystem, avoiding the core waste of "excess inventory" in lean production.

3.3. Equipment IoT and virtual factory

Equipment IoT and virtual factory technology are key to achieving full-process transparency and proactive optimization in production, providing technical support for lean production's "eliminating bottlenecks and continuous improvement."

3.3.1. Data collection and analysis for IoT-enabled equipment

By deploying IoT modules on production equipment (such as machine tools, robots, and sensors), operational data of the equipment (speed, temperature, vibration, machining accuracy, etc.) can be collected in real time and transmitted to the IoT platform for real-time monitoring and anomaly alerts, preventing production interruptions caused by equipment failures (the "waiting waste" in lean manufacturing). At the same time, big data analysis of equipment efficiency (OEE) can identify reasons for low equipment utilization (such as long changeover times or frequent minor stoppages) and propose optimization measures (such as applying quick-change tools and preventive maintenance plans).

3.3.2. Simulation and optimization of virtual factories

Based on real production data collected through IoT-enabled equipment, a digital twin model of the physical workshop is built on the virtual factory platform at a 1:1 scale. The production process (such as production line layout, process routes, and material flow) is simulated. Virtual simulation allows for the early identification of production bottlenecks (such as insufficient capacity at certain workstations or congestion in logistics paths) and testing of optimization solutions in a virtual environment (such as adjusting production line layout or optimizing process sequences), thereby avoiding costs and production interruptions associated with physical workshop adjustments, achieving lean production through "preemptive improvement" rather than "after-the-fact remedies."

3.4. Big data self-decision making

Big data self-decision technology is the "brain" of the Smart Manufacturing system. By integrating data from various subsystems, it enables "lean and automated" production decision-making, driving the transformation of lean production from "human-driven improvement" to "data-driven improvement."

3.4.1. Comprehensive data integration

The big data decision-making subsystem aggregates data from all dimensions, including human resources, production, inspection, distribution, and equipment, to build a unified data warehouse. Through data cleaning and standardization, it ensures the accuracy and consistency of the data, providing a reliable data foundation for decision-making.

3.4.2. Construction of the self-decision algorithm model

Based on the core objectives of lean production (such as OEE improvement, cost reduction, and quality enhancement), a multi-objective optimization algorithm model is constructed. For example: automatically adjusting equipment processing parameters according to equipment operation data and production task requirements to improve efficiency; automatically optimizing raw material ratios based on quality data and raw material data to reduce defect rates; and automatically adjusting scheduling plans based on labor efficiency data and production plans to achieve optimal labor productivity.

3.4.3. Decision execution and feedback

The optimization plans generated by the self-decision algorithm are automatically distributed to various subsystems via API interfaces (e.g., adjusting equipment parameters in the intelligent production subsystem, modifying schedules in the workforce optimization subsystem). At the same time, the execution effects of the decisions (such as efficiency improvement and cost reduction ratios) are monitored in real-time, and the algorithm model is continuously optimized through a closed-loop feedback mechanism to ensure that decisions always align with the lean production goal of "continuous improvement."

4. Conclusion

The construction of a Smart Manufacturing system under the lean production model should take "lean thinking as the soul and intelligent technology as the instrument." Through the framework design of "5 subsystems and 88 tools", it aims to achieve rule coverage and collaborative operation across the entire production process. At the same time, by focusing on the implementation of core technologies such as AI intelligent inspection, unmanned delivery, equipment IoT, virtual factories, and big data decision-making, it promotes the transformation of Smart Manufacturing from "system construction" to "value creation." Future research can further enhance the collaborative precision between subsystems and explore the integration of Smart Manufacturing systems with upstream and downstream supply chains, extending lean production from "within the factory" to "the entire supply chain", thereby building a broader Smart Manufacturing ecosystem.

Disclosure statement

The author declares no conflict of interest.

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