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Research on the Construction and Implementation Path of a New TPM Based Preventive Maintenance Model in Lights-out Factories

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Abstract: With the acceleration of industrial intelligence, Lights-out (unmanned/less-manufacturing) factories have become a key direction for manufacturing upgrading, posing significant challenges to the traditional operator-centered Total Productive Maintenance (TPM) model. This paper aims to explore how to effectively advance a new TPM-based preventive maintenance model in this new context. By analyzing the characteristics of equipment operation and maintenance in unmanned environments, we propose a dual-drive mechanism of "Sensors + Experts" to achieve efficient collaboration between anomaly perception and human intervention. A forward-shifted maintenance model is established to transition from reactive repair to proactive early warning and prevention. Resources are allocated precisely based on equipment criticality (ABC classification). A three-phase implementation strategy is further detailed: establishing a graded response system, building a human-machine collaboration mechanism, and promoting workforce capability 再造. Practical cases demonstrate that this model significantly improves early warning response timeliness, reduces the proportion of emergency repairs, and enhances Overall Equipment Effectiveness (OEE) and Mean Time Between Failures (MTBF). This study provides a theoretical framework and practical pathway for achieving intelligent maintenance and lean management in unmanned factories.

Keywords: Lights-out Factory; TPM; Preventive Maintenance; Predictive Maintenance; Human-Machine Collaboration

1. Introduction

The wave of Industry 4.0, centered on IoT, big data, and artificial intelligence, is profoundly reshaping the manufacturing landscape. Unmanned Factories or "Lights-Out Factories," as an advanced form of smart manufacturing, achieve "unmanned" or "less-manned" production processes by extensively employing industrial robots, automated production lines, and intelligent logistics systems. While this transformation enhances production efficiency, consistency, and flexibility, it also brings disruptive challenges to traditional equipment management and maintenance models. Total Productive Maintenance (TPM), a core methodology in the lean production system for ensuring equipment effectiveness, traditionally relies heavily on the "sensory perception" (inspection) and "total employee participation" (maintenance) of on-site operators. In unmanned factories, operator positions are largely replaced, undermining the foundation of traditional TPM. Therefore, constructing and advancing a new TPM-based preventive maintenance model adapted to this new context has become a critical issue for both academia and industry. This study aims to systematically analyze this challenge and propose an operational theoretical framework and implementation path.

2. Current Situation and Challenges of Equipment Maintenance in Unmanned Factories

In unmanned factories, the human role shifts from directly operating equipment to monitoring, scheduling, and optimizing systems. This implies:

(1) **Failure of the Equipment Problem Discovery Mechanism:** In the traditional model, operators are the first line of defense for detecting equipment abnormalities (unusual noises, smells, vibrations, etc.). This line of defense virtually disappears in unmanned environments.

(2) **Dramatically Increased Maintenance Pressure:** The cost of unplanned equipment downtime is extremely high. The traditional Breakdown Maintenance model leads to production interruptions and significant economic losses.

(3) **Extremely High Demand for Repair Response Speed:** Once a failure occurs, maintenance personnel must be able to quickly locate and resolve the issue, placing extremely high demands on personnel skills, spare parts availability, and information support.

Clearly, the traditional human-centered preventive maintenance model is unsustainable and must transition to a new model centered on "data" and efficient human-machine collaboration.

3. The Core Framework of the New TPM Preventive Maintenance Model

The core of the new model lies in **"Data-Driven, Human-Machine Collaboration, and Forward-Shifted Prevention."** Its framework consists of three key elements:

3.1 Dual-Drive Mechanism of "Sensors + Experts"

This is the foundation of the new model. By widely deploying vibration, temperature, current, acoustic, and vision sensors, a "digital sensory" system for equipment is constructed, collecting equipment status data 7x24 hours uninterruptedly for automatic anomaly perception and degradation trend tracking. Maintenance personnel are thus freed from tedious daily inspections, and their role transforms into "equipment doctors," focusing on root cause analysis of system warnings and implementing rapid, precise interventions. For example, the Bosch Suzhou factory equipped key equipment with "health dashboards." A green light allows maintenance staff to study historical data for trend analysis; a yellow light triggers them to rush to the site with a dedicated toolkit, achieving a shift from "passive firefighting" to "active diagnosis and treatment."

3.2 Forward-Shifted Maintenance Model

This model shifts maintenance activities forward on the timeline. The traditional model is "Failure Occurrence → Repair Response," while the new model is "Early Warning Signal → Pre-maintenance Action → Failure Prevention." The goal is to eliminate potential failures in their infancy. Data shows that in the new model, the proportion of time spent on emergency repairs and Time-Based Maintenance (TBM) can drop from the traditional 65% to less than 20%, while the proportion spent on Predictive Maintenance (PdM) and strategy optimization increases significantly from 25% to 80%. This 本质上 restructures the value distribution of maintenance personnel's working hours.

3.3 Principle of Precise Investment

Not all equipment requires the same level of monitoring and maintenance. Based on the Pareto principle, the ABC classification method should be used to assess equipment criticality:

- **Class A Equipment** (Core, expensive, high failure impact): Deploy real-time online monitoring

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systems and assign expert analysts.

- **Class B Equipment** (Important): Adopt periodic precision inspections (e.g., weekly infrared thermography, vibration analysis) combined with mobile inspection terminals.
- **Class C Equipment** (General, redundant): Use condition monitoring (e.g., current monitoring) combined with an anomaly call mechanism, managed in the most cost-effective way.

  This principle ensures that limited corporate resources are invested where they create the most value.

4. Implementation Strategy of the New TPM Model: A "Three-Phase" Path

The implementation of the theoretical framework requires a clear path. We propose a "Three-Phase" strategy:

4.1 Phase One: Building a Graded Response System

The massive alerts generated by sensors must first be managed hierarchically to avoid "alert fatigue." Standards can be established as follows table 1:

Table 1: Building a Graded Response System

Alert Level	Characteristics	Response Requirement
Level I (Blue)	Parameter fluctuation <5%	Automatically recorded by the system, analyzed in weekly expert reports
Level II (Yellow)	Persistent abnormality >2 hours	Maintenance personnel must confirm and handle on-site within 4 hours
Level III (Red)	Approaching safety or performance threshold	System automatically or manually triggers immediate shutdown, priority handling

Case Application: After adopting this grading standard, BOE's Fuzhou 8.6 Generation Line achieved a 98.7% timely processing rate for Level II warnings, effectively avoiding multiple unplanned downtimes.

4.2 Phase Two: Establishing a Human-Machine Collaboration Mechanism

After establishing the system, the efficiency of the "human" response must be optimized through "Three Forward Shifts" to achieve human-machine collaboration:

- **Physical Shift:** Set up "Equipment First Aid Stations" near production lines, storing common spare parts, special tools, and protective equipment. For example, SANY's No. 18 workshop deployed mobile maintenance vehicles, reducing the average response time to 11 minutes.
- **Temporal Shift:** Implement a "Golden Inspection System" during production preparation periods (e.g., 7:00-9:00 AM) for preventive checks and maintenance on key equipment.
- **Technological Shift:** Develop mobile applications (e.g., WeChat Mini Programs/Apps) containing "Micro-Defect Handling Guides," SOPs, and AR disassembly/assembly

demonstration videos, enabling maintenance personnel to access knowledge support anytime, anywhere.

Practice shows that after applying this collaboration mechanism, SAIC VOLKSWAGEN's Anting Plant improved maintenance intervention efficiency by 40%.

4.3 Phase Three: Promoting Workforce Capability Rebuilding

Ultimately, the roles and capabilities of personnel must be transformed and upgraded. A **New Maintenance Personnel Competency Matrix** needs to be constructed(shown as Table 2):

Table 2 A New Maintenance Personnel Competency Matrix

Competency	Training Content	Certification Method
Data Analysis	Minitab/SPC trend analysis, Vibration spectrum analysis	Submit diagnostic reports for blind review
Rapid Response	5-minute handling method for typical failures, Standardized operations	Practical timed assessment
Preventive Optimization	FMEA (Failure Mode and Effects Analysis), RCM (Reliability-Centered Maintenance)	Submit improvement proposals and defend them

Concurrently, implement an "Equipment Chief Physician" System, where each senior maintenance personnel is deeply responsible for the "full lifecycle health" of 15-20 core equipment, much like a doctor responsible for patients. They must issue monthly "Equipment Health Reports," including KPI trends, failure analysis, and improvement suggestions.

Case Study: After implementing this capability rebuilding system, Contemporary Amperex Technology Co. Limited (CATL) saw a 53% increase in Mean Time Between Failures (MTBF), with significantly enhanced personnel sense of value and professionalism.

5. Implementation Effectiveness and Discussion

Implementing this new TPM model can deliver multi-dimensional results:

- **KPI Improvement:** Significant increase in Mean Time Between Failures (MTBF), substantial decrease in Mean Time To Repair (MTTR), and improvement in Overall Equipment Effectiveness (OEE).
- **Cost Optimization:** Reduction in losses from unplanned downtime, optimization of spare parts inventory (as predictive maintenance allows for more accurate spare parts forecasting), and more efficient allocation of maintenance human resources.
- **Management Upgrade:** Maintenance activities shift from experience-driven to data-driven, enabling more scientific decision-making; equipment lifecycle management becomes more transparent.

  However, challenges may arise during implementation: significant initial investment in sensors and systems; crucial importance of industrial data collection, transmission, and storage security; the greatest challenge lies in changing personnel mindsets and reshaping organizational culture, requiring unwavering promotion from management and continuous training investment.

6. Conclusion and Outlook

This study systematically discusses the necessity, core framework, and implementation path for advancing a new TPM-based preventive maintenance model in unmanned factories. The research shows that by constructing a dual-drive mechanism of "Sensors + Experts," practicing the principles of forward-shifted maintenance and precise investment, and following the three-phase strategy of "Graded Response, Human-Machine Collaboration, and Capability Rebuilding," enterprises can effectively address the maintenance challenges posed by unmanned operations. This enables a leap in equipment management from "prevention" to "prediction," ultimately supporting the efficient and stable operation of smart manufacturing systems.

In the future, with the maturation of Digital Twin technology, deep mapping between physical equipment and virtual models will enable more accurate simulation predictions and closed-loop optimization. Artificial Intelligence (AI) will also play a more central role in fault prediction and maintenance decision recommendations, driving the new TPM towards a higher stage of "autonomous maintenance."