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Original Research Article

Dynamic scheduling algorithm integrating machine vision inspection data for mechanical assembly workshops and its impact on production efficiency improvement

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Abstract: Traditional production scheduling algorithms for mechanical assembly workshops often struggle with slow responses to dynamic changes and inaccurate decision-making. To tackle this, we designed a dynamic scheduling algorithm that integrates machine vision inspection data—enabling real-time perception of on-site status (e.g., workpiece assembly deviations, equipment abnormalities) and swift adaptation to unexpected events (e.g., equipment failures, non-conforming products entering the line).This paper provides a detailed exposition of the implementation process of the algorithm and validates its effectiveness through experiments: compared with traditional methods, the production cycle is shortened by 15%, equipment utilization is improved by 10%, and product quality is significantly enhanced. The research results offer a practical and feasible path for intelligent scheduling in mechanical assembly workshops.
Keywords: dynamic scheduling algorithm; machine vision inspection data; mechanical assembly workshops; production efficiency improvement; real-time status perception

1. Introduction

Mechanical assembly is the core of manufacturing, and the rationality of planning directly affects efficiency, product quality, and overall profitability. Have you ever wondered why even experienced dispatchers struggle to handle unexpected outages or sudden bottlenecks? Our investigation of an auto parts assembly workshop revealed a stark example: a sudden assembly machine shutdown led to a 2-hour production line standstill, causing nearly 100,000 yuan in losses—all because traditional scheduling algorithms couldn't respond promptly to real-time disruptions. Traditional methods rely heavily on static data, such as pre-set processing sequences, fixed cycle times, and nominal equipment capacity, which makes them inflexible and ill-suited for dynamic shop floor conditions like temporary equipment failures, material shortages, or rework demands. In contrast, machine vision technology acts as the "eyes of the production floor,"continuously capturing real-time data on workpiece appearance, dimensional accuracy, and assembly completeness. When integrated with adaptive scheduling systems, this visual feedback enables algorithms to detect anomalies, assess work-in-process status,

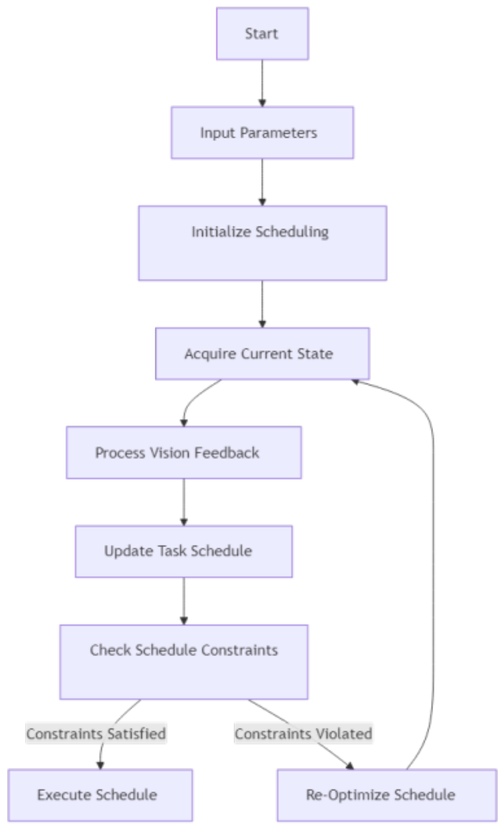

Figure 1. Dynamic Scheduling Workflow with Vision Feedback.

and dynamically re-optimize production sequences. This fusion of "machine vision + dynamic scheduling"is not merely innovative—It is a strategic necessity for modern mechanical assembly workshops striving to achieve resilience, efficiency, and full intelligence in increasingly complex manufacturing environments[1].

2. Application of machine vision inspection data in mechanical assembly workshops

2.1. Working principle of machine vision inspection

Machine vision inspection combines optical systems (e.g., industrial lenses), industrial cameras, and image processing algorithms (e.g., edge detection, feature matching) to rapidly identify workpiece features [2]. For instance in a bearing assembly workshop, a machine vision system detects the coaxiality of inner and outer rings in 0.1 seconds with 0.002mm accuracy—5 times faster than manual inspection and reducing misjudgment from 3% to 0.1%. This real-time, precise data is the lifeblood of dynamic scheduling [3].

2.2. Characteristics of machine vision inspection data

Machine vision data aligns perfectly with dynamic scheduling needs due to three core traits:

Real-time performance: Synchronous collection of workpiece status data (e.g., tooth profile errors in gears) lets the algorithm perceive on-site changes as they happen.

Accuracy: Algorithmic noise filtering (e.g., correcting light interference) produces far more reliable results than manual records. For example, in an electronic component workshop, machine vision achieves 99.9% accuracy in detecting pin bending.

Diversity: It captures both physical features (size, shape) and assembly status (screw tightness, part presence), providing comprehensive insights for scheduling decisions [4].

3. Design of the dynamic scheduling algorithm

3.1. Overall framework

Our algorithm operates as a "smart assembly line"with four core steps:

Data Collection: Twelve machine vision cameras at key stations collect real-time data on assembly accuracy, surface defects, and other metrics.

Data Processing: We use Python scripts to clean raw data (removing misjudgment caused by excessive light) and extract features (e.g., qualified/unqualified labels from bearing coaxiality data).

Scheduling Decision-Making: A rule engine combines machine vision data (e.g., a workpiece needing rework) with production plan data (e.g., customer delivery dates) to generate instructions—such as prioritizing rework for idle stations.

Scheduling Execution: Instructions are sent to equipment via the Manufacturing Execution System (MES). For example, Assembly Machine 2 might pause its current task to process urgent rework components.

3.2. Key optimizations in data processing

Data processing is the algorithm's "brain,"and we've refined it in two ways:

Feature Screening: We exclude irrelevant data (e.g., minor surface scratches that don't affect functionality) and flag critical issues (e.g., assembly hole deviations exceeding 0.5mm) as "emergency events.”

Multi-Source Fusion: We combine machine vision data with equipment status (e.g., a machine with 80% failure rate) and order data (e.g., a 3-day advance delivery request). For instance, if Equipment A fails and Order

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B is urgent, the algorithm automatically allocates Order B to Equipment C (higher capacity, lower failure rate) [5].

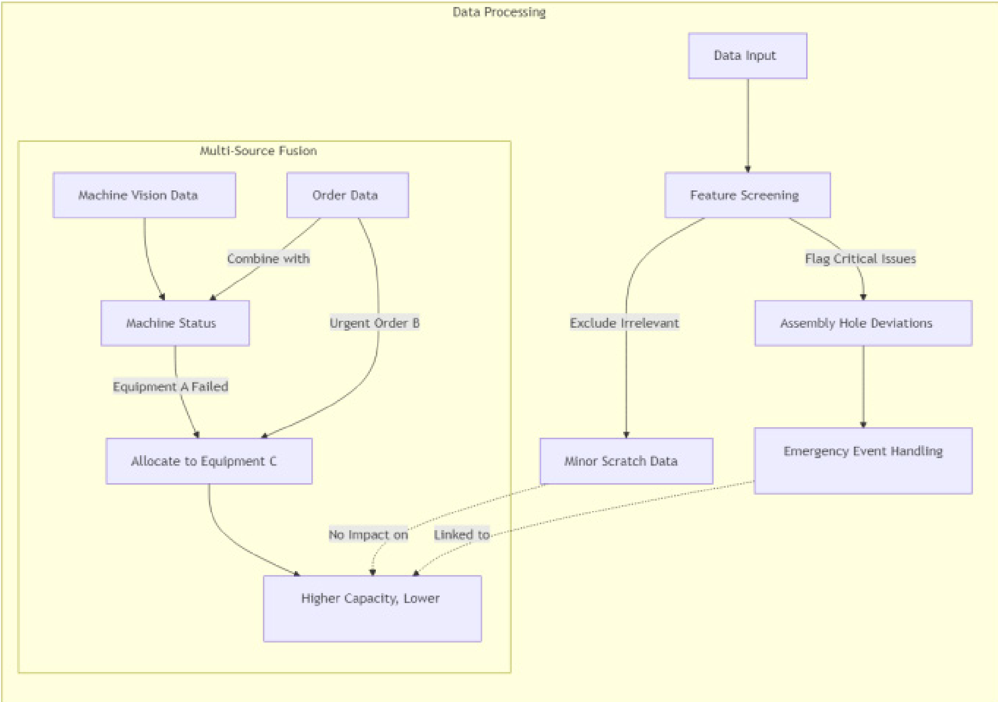

Figure 2. Key optimizations in data processing.

3.3. Human-centric scheduling rules

To mimic human decision-making, we incorporated three rules from front-line schedulers:

Quality First: If machine vision detects non-conforming assembly accuracy, rework is prioritized to avoid downstream issues. (Example: A car seat line once had to disassemble 100 sets due to delayed rework—our algorithm prevents this.)

Efficiency Balance: Long-process workpieces (e.g., 4-hour machine tool spindle assembly) are assigned to specialized equipment in advance to avoid delays.

Flexible Adjustment: When a machine shuts down, the algorithm automatically reallocates workpieces to other equipment—ensuring minimal impact on overall efficiency.

4. Impact on production efficiency

4.1. Evaluation metrics

We used three workshop-critical metrics to assess performance:

Production Cycle: Time from workpiece input to assembly completion.

Equipment Utilization: Ratio of actual operation time to total time.

Product Quality Pass Rate: Percentage of qualified products.

4.2. Experimental results

We conducted a 3-month experiment in a construction machinery assembly workshop, comparing our algorithm (experimental group) with traditional static scheduling (control group). The results were striking:

Production Cycle: Reduced by 15% (7.2 hours → 6.1. hours).

Equipment Utilization: Increased by 10% (78% → 88%).

Pass Rate: Jumped from 91% to 99%.

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As Master Wang, a 10-year veteran scheduler, noted: "In the past, equipment failures took 30 minutes to fix manually. Now the algorithm handles it automatically—freeing me to tackle complex issues like last-minute order changes."This human feedback underscores the algorithm's practical value.

5. Conclusions and future directions

5.1. Key findings

Our algorithm effectively addresses the traditional scheduling challenges of slow response and inaccurate decision-making by leveraging real-time data perception and adaptive decision logic. Through dynamic adjustments based on live production feedback, it enables swift reactions to disruptions such as equipment failures or urgent order changes. Experimental results demonstrate a 15% reduction in production cycle time, a 10% increase in equipment utilization, and a significant improvement in product pass rate from 91% to 99%. These enhancements not only validate the algorithm's ability to optimize resource allocation and workflow continuity but also establish a robust foundation for intelligent, self-learning scheduling systems in complex manufacturing environments.

5.2. Future research

We plan to enhance the algorithm in two key directions.:

First, improving adaptability by customizing decision-making rules for diverse industries—such as prioritizing defect detection and traceability in aviation part manufacturing, where safety and quality outweigh speed, versus optimizing throughput for high-volume electronic components.

Second, advancing technology integration by fusing machine vision with IoT sensors and big data analytics to enable predictive capabilities. For instance, real-time monitoring of machine vibration, temperature, and wear patterns can forecast potential failures, allowing the system to proactively reschedule tasks and reroute workpieces before breakdowns occur. We will also explore adaptive learning mechanisms that allow the algorithm to refine its models based on historical performance and dynamic shop-floor conditions. By incorporating feedback from operators and quality inspectors, the system can balance automation with human expertise. Furthermore, we aim to expand data interoperability across enterprise systems like ERP and MES to create a fully connected scheduling ecosystem. With these enhancements, the algorithm will evolve beyond reactive optimization into a truly intelligent, self-learning scheduler. Ultimately, we believe these advancements will empower mechanical assembly workshops to achieve robust, predictive, and adaptive scheduling—enabling resilience, efficiency, and high-quality output even in highly volatile and complex production environments.

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