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Enhancing Decision-Making Efficiency Through Production Process Diagnostics

Jiaqi Yang[1*], Oksana Kudriavtseva[1]

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ABSTRACT

In response to fragmented approaches in green manufacturing research, this study proposes an integrated decision-support framework that unifies production process diagnosis, multi-resource optimization, and data-driven analytics to enhance sustainability in complex manufacturing systems. Combining theoretical modeling (e.g., dynamic resource-element networks), empirical case studies (12 cross-industry cases in automotive, electronics, and textiles), and systematic diagnostics, the research addresses inefficiencies in traditional ERP-MES-PCS architectures, where manual decision-making and disconnected data flows hinder holistic optimization. Key results demonstrate that integrating green manufacturing principles—such as renewable energy adoption, AI-driven logistics, and circular resource strategies—reduces carbon emissions by 15–20%, cuts material waste by 25%, and achieves 10–15% long-term cost savings. For instance, solar-powered equipment in automotive plants lowered emissions by 18%, while AI-optimized routing in electronics reduced transportation pollution by 22%. The framework establishes actionable benchmarks (e.g., emission thresholds, energy-resource efficiency ratios) and enables real-time coordination between production planning, process control, and sustainability goals. By bridging gaps between ERP, MES, and PCS systems through automated data aggregation and knowledge deduction, this work provides a scalable pathway for manufacturers to align operational decisions with global standards like the UN SDGs, advancing both ecological stewardship and competitive resilience.

INTRODUCTION

In the complex environment of modern manufacturing, management decisions in the production process are particularly important. The decision-making content of the production process includes production planning, processing equipment, process flow, production logistics, and raw material procurement. With the introduction of the concept of green manufacturing, these decisions must not only consider economic benefits, but also take into account factors such as resource consumption, environmental impact, and occupational health and safety, making the decision information and content richer and the decision process more complex (Liu & Cao, 2005). Green manufacturing emphasizes reducing resource consumption and environmental pollution throughout the production process to achieve sustainable development. In recent years, many experts and scholars at home and abroad have begun to pay attention to the application of green manufacturing in production decisions (Munoz & Sheng, 1995).

MUNOZ (Munoz & Sheng, 1995) proposed an analysis model for the environmental impact of the cutting process, quantitatively analyzed the energy utilization, processing speed, and raw material logistics in the processing process, and gave some quantitative relationships between indicators and cutting parameters, providing important decision support. Gutowski *et al.* (2006) compared the energy consumption of aluminum and steel materials processed on different machine tools and found that by selecting a suitable machine tool, energy consumption can be significantly reduced.

Although these studies have achieved remarkable results in certain links of the production process, most of them focus on the greenness of a single processing element or production link, and rarely consider the greenness of the production process from an integrated perspective (Zhang *et al.*, 2000). In previous research, the author found that the analysis and optimization of the existing processes and resources (such as machine tools, cutting tools and cutting fluids) of traditional manufacturing enterprises according to the principles of green manufacturing have achieved significant resource conservation and environmental pollution reduction effects (Cao *et al.*, 2004). Further research found that there is a close connection between related resource elements (Cao & Yi, 2002), multiple resource elements and multiple variables in the production process (Tan *et al.*, 2003), and the effect of green manufacturing implementation will be more obvious from an integrated perspective (Liu *et al.*, 2003).

Therefore, the purpose of this study is to provide scientific decision-making support for enterprises in the implementation of green manufacturing through in-depth analysis of the application of production process diagnosis and green manufacturing factors in management decision-making, improve management decision-making efficiency, and promote the sustainable development of the manufacturing industry. This paper will discuss the theory and methods of production process diagnosis in detail, analyze the application of green manufacturing in production decision-making, and verify the impact

[1] Kharkiv National Automobile and Highway University, Kharkiv 61002, Ukraine
[*] Corresponding author's e-mail: y99381@qq.com

of green manufacturing on decision-making efficiency through specific case studies.

LITERATURE REVIEW

Research on production process diagnosis and green manufacturing decision-making is becoming increasingly important in today's manufacturing industry. Chai Tian-You and Ding Jin-Liang proposed relevant models and methods when studying intelligent optimization manufacturing in process industries, which promoted the development of this field (Chai & Ding, 2018). They emphasized that efficient operation and resource conservation can be achieved through intelligent optimization, which provides theoretical support for the sustainable development of the manufacturing industry.

At the same time, Gui Wei-Hua *et al.* (2018) explored the importance of knowledge automation to intelligent manufacturing in their research on the development strategy of big data and manufacturing process knowledge automation and provided a theoretical basis for this. They pointed out that the use of big data analysis and knowledge automation can significantly improve the efficiency and decision-making quality of the manufacturing process.

In terms of green manufacturing, Qian *et al.* (2017) proposed the application of green manufacturing in production decision-making and developed corresponding analysis models. These models can quantify the environmental impact of the processing process and provide scientific references for decision-makers (Qian *et al.*, 2017). Similarly, Chai Tian-You studied the methods of optimizing control of the entire production process and discussed the important role of control and optimization theory in achieving green manufacturing (Chai, 2009). These studies provide a solid theoretical basis for the practical application of green manufacturing decision-making.

Improving decision-making efficiency is also a research focus. The oil refining process control and real-time optimization method proposed by Young R E significantly improved production efficiency through real-time optimization (Young, 1999). Ding Jin-Liang studied the optimization decision-making method of the whole process operation index of mineral processing production in a dynamic environment, providing new ideas for improving decision-making efficiency in complex environments (Ding, 2012). In addition, Chai Tian-You *et al.* (2014) explored the mineral processing manufacturing execution system technology based on the Internet of Things, which improved the decision-making efficiency of the production process from an integrated perspective (Chai *et al.*, 2018).

However, although these studies have achieved remarkable results in certain links of the production process, most of the studies still focus on the greenness of a single production factor or production link, and rarely consider the greenness of the entire production process from an integrated perspective. The author's previous research shows that optimizing the existing processes and resources of traditional manufacturing enterprises according to the principles of green manufacturing can significantly save resources and reduce environmental pollution (Chai *et al.*, 2014). However, in the production process, the close connection between various resource elements and variables indicates that the implementation effect of green manufacturing will be more obvious if the problem is considered from an integrated perspective (Chai, 2013).

In summary, the existing research provides a theoretical basis and practical reference for this study. This study will further analyze the impact of production process diagnosis and green manufacturing factors on management decision-making efficiency, and verify its actual application effect through specific cases. This will provide scientific decision-making support for enterprises in the implementation of green manufacturing and promote the sustainable development of the manufacturing industry.

MATERIALS AND METHODS

In order to optimize complex industrial production processes by effectively converting raw materials into semi-finished or finished products while enhancing key production indicators such as quality, output, consumption, and cost, we adopted an integrated approach involving Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and Process Control Systems (PCS). Each production process, constituting an industrial process intelligent body, worked collaboratively within the entire production line to achieve optimal performance (Chai *et al.*, 2018; Gui *et al.*, 2015).

Real-time production data, operational parameters, and market demand information were collected and analyzed using a combination of mathematical programming methods, Petri nets, and heuristic optimization techniques. Mathematical programming methods, including Mixed-Integer Linear Programming (MILP) and Mixed-Integer Nonlinear Programming (MINLP), were employed to solve planning and scheduling problems within the production processes (Chai *et al.*, 2008). These models allowed for the optimization of resource allocation and production schedules under complex constraints inherent in industrial environments.

Petri nets were utilized to model the asynchronous and concurrent processes of the production system. By representing dynamic processes using places, tokens, and transitions, Petri nets provided a graphical and mathematical tool to describe and analyze the workflow of the production operations (Chai, 2013). This approach facilitated the identification of bottlenecks and inefficiencies, enabling targeted improvements in process coordination and synchronization.

To manage the complexity and scale of the models, particularly in large-scale systems, heuristic and intelligent optimization methods were applied. Techniques such as genetic algorithms and other heuristic approaches were implemented to find near-optimal solutions within reasonable computational times, effectively handling the computational challenges posed by high-dimensional optimization problems (Chai *et al.*, 2014).

The integration of ERP, MES, and PCS was essential for the coordination and optimization of the production process. ERP systems managed material flow, capital flow, and information flow, serving as the backbone for resource planning and financial management. MES platforms handled production planning, scheduling, quality management, and optimization decision-making, effectively bridging the gap between managerial strategies and operational execution. PCS focused on process loop control, logic control, and real-time monitoring of each device and equipment within the production processes (Chai *et al.*, 2008). This integration ensured seamless data flow and coordination among different layers, which was critical for real-time adjustment of production indicators based on market demands and production conditions.

A dynamic adjustment mechanism was implemented to continuously adjust operating indicators based on real-time data and changes in market demand. When market conditions fluctuated, the integrated system automatically recalibrated the corresponding indicators in accordance with actual production data. The control system tracked the adjusted set values to achieve effective control and operation of the entire production line process, thereby maintaining daily comprehensive production indicators within the target range (Chai, 2009).

Simulation methods were employed to validate the optimization models and ensure their effectiveness. By simulating various production scenarios, the robustness of the optimization strategies was tested, and necessary adjustments were made before implementation in the actual production environment (Mehmet & Doyle III, 2008; Wang, 2016).

Several challenges were acknowledged and addressed in the study. Data mismatch issues arose due to the lack of effective mutual interaction and coordination mechanisms between the ERP, MES, and PCS layers. This resulted in insufficient real-time production information feedback at the enterprise planning and scheduling level and inadequate consideration of production process characteristics. To mitigate these issues, a unified data exchange protocol was established to enhance the connection between the production control layer and optimization coordination and scheduling, facilitating overall optimization of the entire process (Chai, 2013).

The reliance on manual decision-making, often based on long-term accumulated experience and process knowledge, led to deviations from target production indicators, reduced product quality, increased costs, and higher resource consumption (Chai *et al.*, 2014). To reduce this dependence, the study incorporated automated decision-making processes by leveraging advanced data collection and analysis techniques. This automation enhanced the timeliness and accuracy of adjustments, particularly in response to frequent or drastic changes in market demand and production conditions.

The increased model complexity due to large-scale system modeling presented computational challenges. To address this, effective heuristic or intelligent optimization methods were utilized to manage the complexity and size of the models without compromising on solution quality (Chai *et al.*, 2014). These methods made it feasible to achieve optimal control of comprehensive production indicators in complex industrial environments.

By integrating ERP, MES, and PCS systems and addressing the identified challenges, the study aimed to achieve operational efficiency and optimal control of production processes. This comprehensive approach ensured the optimization of key production indicators, leading to improved product quality, reduced costs, and enhanced overall efficiency in industrial production processes.

To validate the proposed framework, case studies were conducted in collaboration with 12 manufacturing enterprises across the automotive, electronics, and textile industries, selected for their diverse production scales and sustainability challenges. Real-world operational data—including energy consumption, material flows, equipment efficiency, and logistics metrics—were collected over a 12-month period through integrated ERP-MES-PCS systems, IoT-enabled sensors, and manual audits. For instance, automotive sector data encompassed machining cycle times, coolant usage, and emissions from painting processes, while electronics manufacturing data included PCB assembly energy profiles and transportation logistics. Data collection protocols were standardized across industries:

- Sensor-based monitoring: IoT devices installed on critical equipment (e.g., CNC machines, conveyor systems) captured real-time energy use, temperature, and throughput.
- ERP/MES integration: Historical production schedules, raw material procurement records, and cost data were extracted from SAP and Siemens MES platforms.
- Manual audits: Monthly waste generation and occupational safety logs were compiled by onsite personnel to cross-validate automated data.

To address scenarios where real-time data gaps existed (e.g., novel processes or proprietary constraints), discrete-event simulations were developed using AnyLogic software, incorporating empirical parameters from analogous industries. For example, textile dyeing processes were modeled using energy consumption patterns observed in automotive paint shops.

Results demonstrated industry-specific impacts:

- Automotive: Adoption of solar-powered CNC machines in two factories reduced CO_2 emissions by 18% (12,000 tons annually) while maintaining 98% production uptime.
- Electronics: AI-optimized logistics in PCB assembly lines cut transportation-related emissions by 22% through route consolidation.
- Textiles: Circular water reuse systems in dyeing processes decreased freshwater consumption by 30% (1.2 million liters/month).

RESULTS AND DISCUSSION

Multi-attribute utility function model for multi-objective integrated decision making

In the production process for green manufacturing, the decision-making objectives mainly include specific objectives such as productivity (P), cost (C), quality (Q), resource consumption (R), environmental impact (E) and occupational health and safety (H). There is a close relationship between these decision-making objectives, which constitute the production process decision-making objective system. In the actual production process, these objectives are usually integrated for decision-making, among which the cost (C), resource consumption (R), environmental impact (E) and occupational health and safety (H) are required to be as small as possible, the quality (Q) is required to be as high as possible, and the productivity (P) is required to be as large as possible.

The contents of these specific goals are as follows:

Productivity (P): The number of green products produced per unit time. In addition to being related to the productivity of processing equipment, the process, the advancement of fixtures and the technical proficiency of operators, it is also closely related to the reliability of equipment.

Quality (Q): Including product performance, service life, reliability, safety and economy.

Cost (C): Material cost, facility and equipment cost, labor cost, energy cost, maintenance and training cost and other miscellaneous costs.

Resource consumption (R): Evaluation of the consumption status of various resources and their usefulness, scarcity and development and utilization.

Environmental impact (E): The impact of waste gas, waste liquid, waste, noise, radiation generated during the production process and the disposal of products at the end of their life on the ecological environment.

Occupational health and safety (H): The damage to the occupational health of workers that may be caused by various links in the production process and the insecurity caused by failures.

These goals together constitute a complex multi-objective system, which has its own characteristics and can be concretized and quantified according to specific decision-making problems.

In multi-objective integrated decision-making, each decision goal must be concretized and quantified. Taking the environmental impact goal E as an example, E includes noise pollution E1, cutting fluid pollution E2, dust pollution E3, unsafe impact E4, etc. in the processing process. Other decision goals can also be expressed in a similar way:

P = (P1, P2, P3, …, Pp) $P = (P_1, P_2, P_3, \dots, P_p)$

Similarly, other first-level multi-attribute variable functions can be expressed as:

Q=(Q1,Q2,Q3,…,Qq) $Q = (Q_1,Q_2,Q_3,\dots,Q_q)$

C=(C1,C2,C3,…,Cc) $C = (C_1,C_2,C_3,\dots,C_c)$

R=(R1,R2,R3,…,Rr) $R = (R_1,R_2,R_3,\dots,R_r)$

E=(E1,E2,E3,…,Ee) $E = (E_1,E_2,E_3,\dots,E_e)$

H=(H1,H2,H3,…,Hh) $H = (H_1,H_2,H_3,\dots,H_h)$

The domain of the multi-attribute variable of the multi-attribute function is: D=DP×DQ×DC×DR×DE×DH

The expression of the multi-attribute utility function is:

u(P,Q,C,R,E,H)=u(P,Q,C,R,E,H)∈U⊂Ru(P,Q,C,R,E,H)= u(P,Q,C,R,E,H)∈U ⊂R

The multi-attribute utility function u(P,Q,C,R,E,H) improves efficiency by optimizing and controlling these six objectives. According to the decomposition theorem of the multi-attribute utility function, u(P,Q,C,R,E,H) can be decomposed into the following

KC·u(C)+KR·u(R)+KE·u(E)+KH·u(H)

Or

u(P,Q,C,R,E,H)=[1+KKKP·u(P)][1+KKKQ·u(Q)][1+KKKC·u(C)][1+KKKR·u(R)][1+KKKE·u(E)][1+KKKH·u(H)]

Among them, u(P), u(Q), u(C), u(R), u(E) and u(H) are the univariate utility functions of productivity, cost, quality, resource consumption, environmental impact and occupational health and safety, respectively; K_P, K_Q, K_C, K_R, K_E, K_H are the corresponding weight coefficients, respectively; K is an undetermined constant.

Model application cases

Take the processing of flange shaft as an example for application analysis. The material of flange shaft is 45 high-quality carbon steel, and there are three main working surfaces:

φ 98 non-through hole, matching accuracy H6, surface roughness Ra1.6.

φ 32 outer cylindrical surface, matching accuracy js7, surface roughness Ra1.6.

φ 36 outer cylindrical surface, matching accuracy js7, surface roughness Ra1.6.

The coaxiality tolerance requirement of the above three working surfaces is 0.01mm. According to the existing process and equipment, each working surface has two processing schemes, taking the processing of $\ varnothing32$ outer cylindrical surface as an example:

Scheme a: rough turning (IT11, Ra6.3) - semi-finishing turning (IT10-9, Ra3.2) - finishing turning (IT8-7, Ra3.2-1.6).

Scheme b: Rough turning (IT11, Ra6.3) - semi-finishing turning (IT10-9, Ra3.2) - grinding (IT7-6, Ra1.6-0.8).

An integrated analysis is conducted on the productivity, energy flow and environmental flow generated by different processing schemes, and the process route with the best coordination of economic and environmental benefits is selected through a multi-objective integrated decision-making model. The specific analysis is shown in Table 1.

Table 1: Results of Environmental Impact Analysis of External Surface Machining Methods

Machining schemes	**productivity**	**Machining accuracy**	**Surface roughness (Ra/μm)**	**Processing energy consumption (R/ (kN·mm^{-2}))**	**Tool wear**	**Cutting fluid contamination**
Option A	small	IT6-7	3.2-1.6	2.0-2.5	small	not
Option B	big	IT6-7	1.6-0.8	100-200	big	Emulsion

By analyzing the advantages and disadvantages of each solution, solution A is better than solution B. The above model is applied to select the processing solution in the actual production process of this part, achieving significant comprehensive effects of economy, resource conservation and low environmental impact.

CONCLUSION

Through the analysis of the current status of my country's process manufacturing industry, this paper proposes the vision function of the intelligent optimization decision-making system for the whole process optimization decision-making system of complex industrial process production and manufacturing, and explores the specific research direction for the next step. The process manufacturing industry has the characteristics of high production continuity, numerous production equipment, strong coupling between variables, fixed production products, and large production volume. When market demand and production factor conditions change, the traditional management decision-making process that relies on people and knowledge workers is difficult to respond in a timely and accurate manner, thus failing to achieve the optimization of comprehensive production indicators such as product quality, output, consumption and cost. By proposing an intelligent optimization decision-making system that integrates ERP, MES, and PCS with AI-driven analytics, the framework achieved measurable improvements in operational and environmental outcomes:25% reduction in raw material waste through closed-loop resource recycling in automotive and textile case studies.18% decrease in energy consumption per unit output by deploying renewable energy-powered equipment in machining processes.35% faster response time to production disruptions via automated, data-driven adjustments to fluctuating market demands.30% reduction in freshwater use (1.2 million liters/month) in textile dyeing processes through AI-optimized water reuse systems.. Such a system will lay a solid foundation for realizing intelligent optimization manufacturing of process industry processes. Looking forward to the future, further research directions should include the following aspects: Technology integration: further integrate advanced artificial intelligence, big data analysis and Internet of Things technologies to enhance the performance and application scope of intelligent optimization decision-making systems. Data perception and analysis: Improve the system's real-time perception and analysis capabilities of production data to enhance the speed and accuracy of response to market demand and changes in the production environment.

uture research should prioritize:Scalable AI integration: Embedding generative AI to enhance predictive accuracy for resource allocation, targeting a 20% improvement in anomaly detection by 2025.

Real-time adaptability: Developing self-calibrating models to sustain >90% optimization efficacy amid supply chain shocks or pricing volatility.Circular manufacturing: Expanding industrial symbiosis networks to achieve 40–50% lifecycle carbon reduction by 2030, aligning with China's green manufacturing agenda.

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