

Strategies for Production Optimization in Non-Flow Production Models in the Context of the Digital Economy

Yunchang Liu ^a

College of Management and Economics, Tianjin University, Tianjin, China

Keywords: Data-Driven, Smart Manufacturing, Production Optimization, Data Analysis.

Abstract: This underscores the critical importance of enhancing production flexibility and intelligence. The extant research primarily focuses on assembly line production models and has not extensively explored non-assembly line production models. The present study focuses on the application of data empowerment to island assembly models to optimize resource scheduling, production efficiency, and equipment utilization. The research methods employed encompass theoretical modeling and case analysis. A mixed-integer programming model is employed to analyze the role of data empowerment, and an intelligent warehouse system is utilized to validate its effectiveness. A substantial body of research has demonstrated that the empowerment of data leads to a considerable enhancement in the utilization of equipment and optimizes inventory management. This approach contributes to the acceleration of production cycles and the enhancement of process and task completion rates. Furthermore, it facilitates seamless production connections, thereby enhancing system stability and response speed. Moreover, data empowerment enhances system flexibility, thus enabling the system to respond more effectively to market fluctuations and uncertainties. This article demonstrates the importance of data empowerment in manufacturing transformation and the potential for further exploration of data technology integration in various fields.

1 INTRODUCTION

In recent years, the global manufacturing industry has undergone a rapid transition from Industry 3.0 to Industry 4.0. The traditional assembly line production model plays a significant role in large-scale, standardized production. It meets market demand for standardized products with its efficient and scalable characteristics. However, as consumer demand diversifies and market uncertainty increases, the traditional assembly line model is showing its limitations in adapting to small-batch, multi-variety, and personalized production. Traditional models often prove ineffective when it comes to dealing with market demand fluctuations, customized production, and rapid resource allocation. Non-assembly line production models have presented challenges in the face of traditional assembly line models. Data-driven technologies have advantages that make them a potential solution to these problems. These technologies have been adopted widely in

manufacturing, and there is immense potential for them in non-assembly line production. It is critical to conduct in-depth research on the application of these technologies in non-assembly line production to drive the transformation and upgrade of manufacturing and enhance corporate competitiveness. Therefore, how to enhance the flexibility and intelligence of production systems while maintaining high efficiency is a pressing issue that must be addressed in the transformation and upgrading of manufacturing.

To address the challenges, data-empowered technologies are increasingly being recognized as a key method for enhancing production flexibility and intelligence. Data-empowered technologies enable real-time data collection, analysis, and optimization, thereby improving the adaptive capabilities and decision-making efficiency of production systems. This assertion is especially valid in non-assembly line production models, where the optimization of resource scheduling, equipment utilization, and production cycles can effectively address the

^a <https://orcid.org/0009-0001-6754-1018>

complexity and uncertainty inherent in production environments (Li,2025). A significant body of research was conducted by scholars and industry experts on data-empowered technologies, with a particular focus on their application in manufacturing. For instant, the application of data empowerment in flexible production systems can significantly improve production response speed and resource utilization (Zhang,2024). Wu et al. demonstrated through case studies that data empowerment can help enterprises quickly adjust production plans in highly uncertain production environments, thereby maintaining efficient operations (Wu,2025). However, despite the myriad valuable explorations provided by extant research on the application of data empowerment in production systems, the majority of studies concentrated on assembly line production models or specific industries. These studies did not fully consider the potential of data empowerment in non-assembly line production models. Under island assembly models, the question of how to achieve intelligent and flexible production through data empowerment remains a relatively under-researched area. Therefore, filling this research gap and exploring the specific applications and effects of data-driven technologies in non-assembly line production modes holds significant theoretical and practical significance.

The focus of this study is to explore the application of data empowerment in non-assembly line production models, with an emphasis on how it can enhance the flexibility and intelligence of production systems through real-time data collection and optimized decision-making, thereby addressing issues such as uneven resource allocation, equipment idling, and prolonged production cycles. The core of the research lies in integrating the island assembly mode with data empowerment technology, delving into the underlying mechanisms of their combination, and validating their effectiveness through case studies in actual production settings.

Theoretical modeling can reveal the intrinsic mechanisms of data empowerment in non-assembly line production modes from an abstract level, while case studies can validate the effectiveness and feasibility of these mechanisms through actual cases. Therefore, this study comprehensively employs theoretical modeling and case study methods. Specifically, first, through theoretical modeling, based on the characteristics of data empowerment technology and island assembly mode, this study proposes the key mechanisms of data empowerment

in non-assembly line production modes. Second, the specific application effects of data empowerment in resource scheduling, production efficiency, and equipment utilization are explored using optimization tools such as data analysis and mixed integer programming models in combination with a specific smart warehouse case.

The study aims to investigate how data empowerment can optimize non-assembly line production modes, focusing on addressing key challenges such as unbalanced resource allocation, equipment idling, and prolonged production cycles. By systematically analyzing the core differences between non-assembly line and traditional assembly line modes, the study reveals the unique application value and efficiency-enhancing pathways of data empowerment in non-standard production scenarios, and validates its effectiveness in improving production efficiency and resource utilization through actual case studies.

2 OVERVIEW OF NON-ASSEMBLY LINE PRODUCTION MODELS

2.1 Definition and Characteristics of Non-Continuous Production Mode

Non-continuous production mode is a production organization method that does not rely on traditional assembly lines. It is widely used in scenarios involving small batches, multiple varieties, and customized production. This production organization method, which does not rely on traditional assembly lines, has the following notable characteristics: It emphasizes that each unit in the production process can operate independently, and production steps can be flexibly arranged according to product requirements and process characteristics, rather than following a fixed sequence. Unlike traditional assembly line production modes, non-assembly line production modes offer significant advantages in terms of production flexibility and the ability to address diverse demands (Tang,2021), particularly in industries with long production cycles, complex products, and strong customization requirements, such as aerospace manufacturing, shipbuilding, and the production of special equipment.

Under the non-assembly line production model, production tasks are not strictly constrained by fixed

processes, and production units operate independently and flexibly, enabling effective response to production environments characterized by significant market demand fluctuations, diverse product types, and strong personalized customization requirements. This model possesses strong adaptability and production flexibility (Zhang,2022). However, this flexibility also presents challenges in data management and resource allocation. The complexity of non-assembly line production requires enterprises to have more precise scheduling and resource allocation capabilities, especially with the support of intelligent and automated management systems. It is necessary to effectively integrate and optimize the massive amounts of data generated during the production process to improve production efficiency and resource utilization (Wang,2022).

Although non-assembly line production faces greater challenges in resource allocation and production rhythm control compared to assembly line production, it demonstrates unique advantages in handling customized and highly flexible production tasks. By leveraging data-driven capabilities and intelligent scheduling systems, non-assembly line production can meet personalized production demands while improving production efficiency and resource utilization, thereby playing an increasingly important role in modern manufacturing (Chen,2021).

2.2 Data Characteristics in Non-Assembly Line Production Modes

2.2.1 Data Types and Sources

In non-assembly line production modes, intelligent manufacturing systems rely on wireless local area network (WLAN) technology to achieve device interconnection and data collection. System data primarily includes equipment operation, workstation status, material flow, and production rhythm, covering the entire production process.

Data sources primarily include production information management systems, sensors, and central control screens. Specific types include equipment operating status, such as current operation, shutdown, or fault conditions. Production environmental data covers key parameters such as production capacity, air pressure, temperature and humidity, and noise levels. Information for each workstation and unit includes location, power status,

material status, and task progress. Additionally, warehouse location information provides detailed data on storage status, material categories, and storage duration. Through comprehensive monitoring and management of these data, the efficiency and reliability of the production process can be effectively improved (Fang,2021).

Managers can use mobile terminals to monitor workstation and task status in real time, while electronic bulletin boards provide visual monitoring. Digital twin technology enables real-time interaction between the physical status of equipment and virtual models, supporting digital mapping of the entire production process and significantly improving system efficiency and flexibility.

2.2.2 Data Complexity and Correlation

In non-assembly line production modes, the island-based assembly model achieves decoupling and flexible reorganization of assembly processes through modular work units called “islands.” Each ‘island’ is responsible for completing one or a group of relatively independent assembly operations and possesses certain autonomous operations and local optimization capabilities. Under the unified management of the central scheduling system, the “islands” collaborate to complete complex assembly tasks and can dynamically adjust the content and execution order of operations based on real-time production status. It is precisely because of this characteristic of the island assembly model that the data in the production process is highly complex and interrelated.

To achieve this flexible and efficient coordination mechanism, each “island” relies extensively on data-driven analysis methods during operation. First, by collecting real-time data on equipment status and process execution, the system uses correlation analysis to identify resource conflicts, process dependencies, and bottlenecks, guiding dynamic adjustments to assembly rhythms. Second, leveraging mixed-integer programming (MIP) algorithms, the system integrates multiple constraints such as process priorities, resource utilization, and time windows into a unified scheduling model to optimize production scheduling strategies across multiple islands, ensuring globally optimal resource allocation. Third, based on predictive models (such as time-series-based order trend forecasting and inventory demand forecasting), the system can anticipate future production capacity loads and material requirements,

enabling proactive adjustments to assembly plans to mitigate the impact of sudden orders or inventory shortages.

Additionally, some “islands” utilize edge computing devices to locally process high-frequency data such as equipment operational status, sensor feedback, and work-in-progress information, reducing reliance on the central system and accelerating response times. These data analysis and processing mechanisms support the independent operation of “islands” and ensure the entire assembly system maintains high adaptability and robustness in response to dynamic changes in orders, processes, and material conditions.

3 APPLICATION OF DATA EMPOWERMENT IN NON-ASSEMBLY LINE PRODUCTION MODELS

3.1 Role and Mechanism of Data Empowerment

3.1.1 Enhancing Production Efficiency Through Data Empowerment

In a Smart Warehouse environment, the demand for resources among different work islands is highly uncertain, requiring real-time scheduling systems to effectively resolve potential conflicts during frequent resource calls. At the same time, the diversity of data types, such as equipment operating status, material location information, and process progress, significantly increases the complexity of the decision-making process. Faced with constantly changing order demands, the assembly system must have a highly flexible, dynamic adaptation capability to minimize material waste and avoid process delays. To effectively address these issues and enhance the dynamic adaptability of assembly systems, data decomposition has emerged as a critical approach. By decomposing complex data, heterogeneous data can be transformed into basic elements that can be independently identified and analyzed, thereby providing a reliable foundation for analyzing resource requirements and optimizing decision-making processes. Data decomposition helps systems better

identify potential conflicts, optimize resource scheduling, reduce material waste, and avoid process delays.

Initially, the data types involved must be identified and classified. According to the preceding analysis, the present study encompasses the following data types. The initial category is equipment data, encompassing the operational status of equipment, including power status (i.e., on, off, and malfunction), as well as real-time production capacity and environmental parameters such as air pressure, temperature, and humidity. The second category is production data, which encompasses production rhythm, the number of work-in-progress items, and the input and output quantities of materials. The third category is job unit data, which includes the real-time operating status of each job unit, the material information involved, power consumption, and task execution progress. The fourth category is inventory data, which encompasses information regarding temporary storage location, material status, storage-related information, and material storage time. The fifth category is real-time monitoring data, which is primarily obtained through sensors and central control screens to gather real-time information on equipment operation and environmental conditions. Additionally, it encompasses the execution status of tasks, which are ascertained through the utilization of mobile handheld devices.

Following the identification of the data types, it is imperative to undertake a subsequent analysis of the data sources to ensure data completeness and accuracy. Sensors installed on-site enable real-time monitoring of equipment operating status and environmental parameters, thereby ensuring the timeliness and authenticity of the data. The production information management system provides comprehensive production data support and statistical analysis functions, helping to systematically understand production status. Central control screens and electronic bulletin boards are utilized to display the status of equipment and key production indicators in a centralized manner, thereby enhancing the efficiency of information transmission. The implementation of digital twin technology facilitates the real-time mapping of equipment operation within a virtual environment, thereby enabling dynamic simulation and interaction with the status of the equipment. This, in turn, enhances perception and control capabilities over the production process. The overall process is shown in Figure 1.

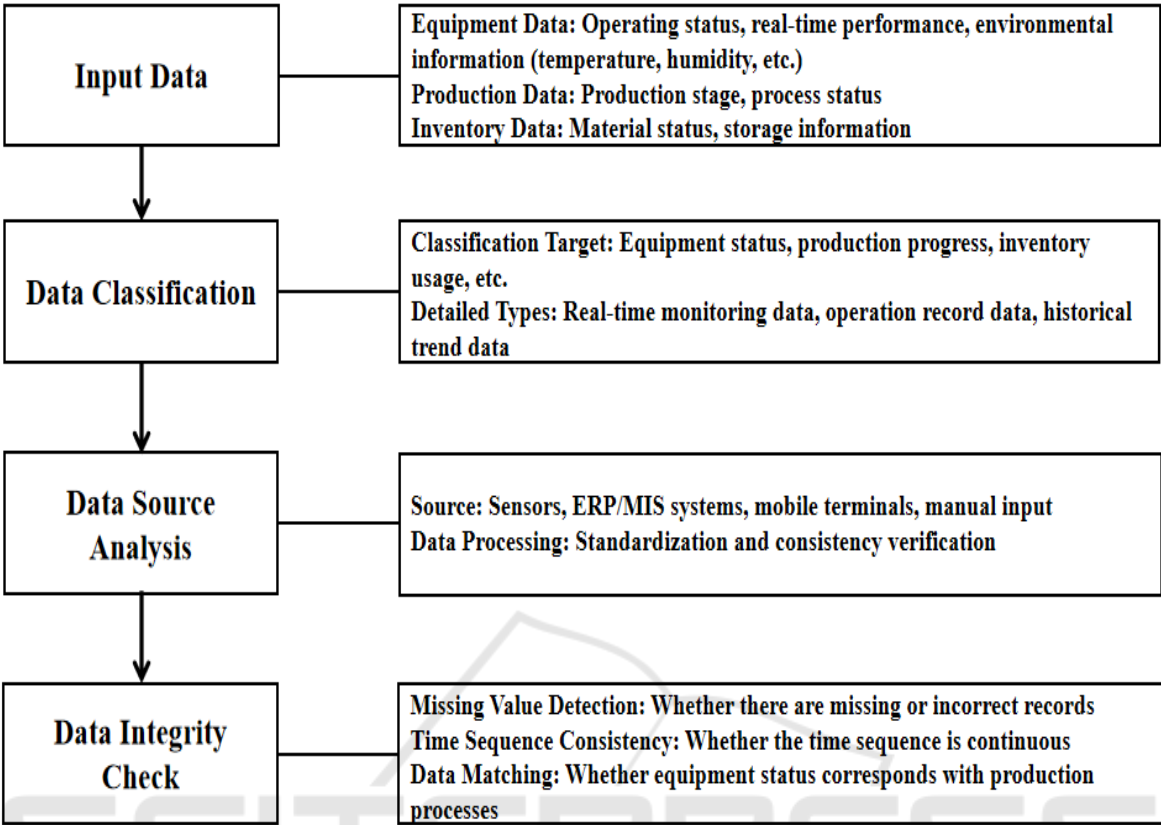


Figure 1: Data decomposition process (Picture credit: Original)

3.1.2 Data Dimensions and Key Performance Indicators

Effective application of data dimensions, and key performance indicators (KPIs) is critical to improving production efficiency in the management and optimization of smart warehouses. Data dimensions offer a thorough analytical view of the production process. They include the time dimension, which identifies time-based patterns to support production decision-making; the equipment dimension, which monitors equipment utilization rates and failure frequencies to mitigate risk; the material dimension, which ensures material flow and supply align with production demands to reduce waste (Fang,2021); the process dimension, which monitors progress to optimize production workflows; and the work unit dimension, which coordinates resources between workstations to enhance flexibility and adaptability. However, data dimensions alone are insufficient for a comprehensive assessment of production efficiency.

Thus, key performance indicators (KPIs) have emerged as essential tools for quantifying the performance of each dimension. Production cycle time measures processing time to help identify bottlenecks and optimize processes. Equipment utilization assesses usage to help identify issues with inefficient use. Inventory turnover rate measures material flow efficiency to avoid inventory buildup. Process completion rate reflects production task execution to help adjust plans. Task execution rate focuses on execution efficiency to ensure the coordinated operation of all production links. Comprehensive utilization of data dimensions and key performance indicators (KPIs) enables companies to enhance production transparency, improve flexibility and efficiency, and make more precise decisions in complex production environments (Zheng,2022). This optimization extends to their overall warehouse management system.

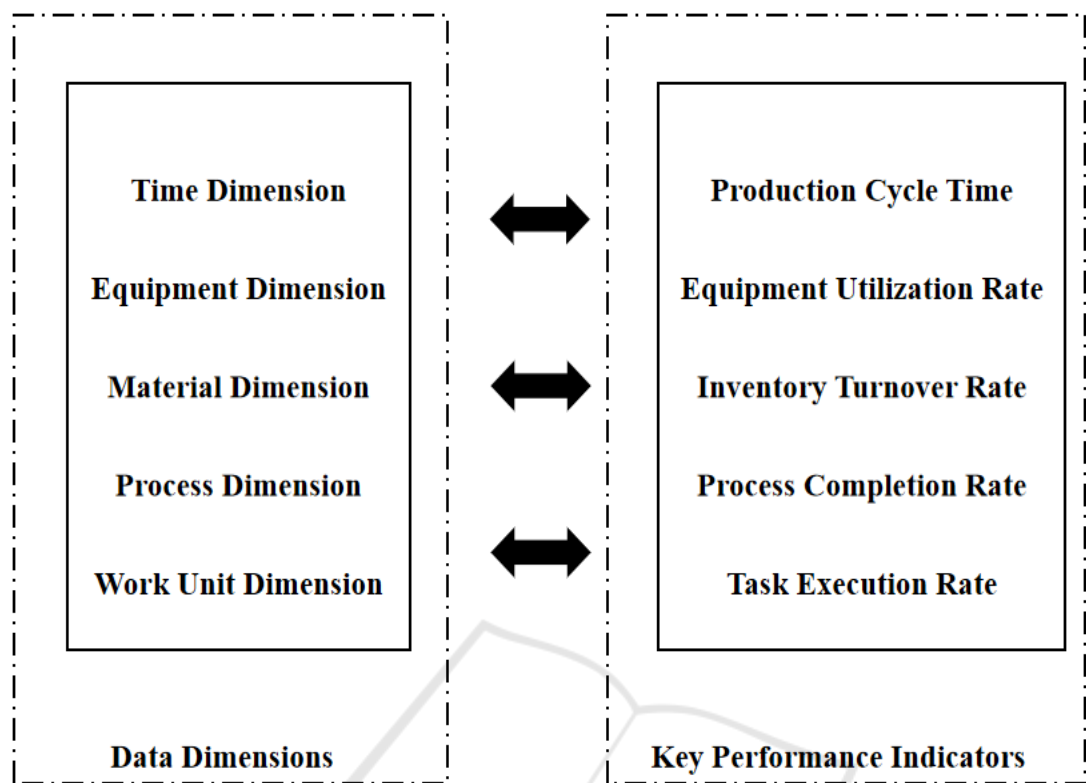


Figure 2: Data dimension and key performance indicator correspondence chart (Picture credit: Original)

A close intrinsic relationship exists between data dimensions and key performance indicators. As shown in Figure 2. Each data dimension provides the necessary contextual data for calculating KPIs. For instance, the level of equipment utilization is directly influenced by the operational status within the equipment dimension. Frequent equipment malfunctions result in a significant decrease in equipment utilization, potentially indicating underlying resource scheduling issues. Concurrently, the length of the production cycle time is closely related to the processing time of each process in the time dimension, which can reveal bottlenecks in the production process. Furthermore, the integration of inventory turnover rate with real-time data from the material dimension can facilitate the formulation of rational material replenishment and allocation strategies by management, thereby enhancing the overall efficiency of the production system (Zheng,2022). Through meticulous examination of these dimensions and indicators, smart warehouses can attain more efficient resource scheduling and decision support.

To further enhance the operational efficiency of smart warehouses, effective correlation analysis is imperative. The objective of correlation analysis is to

explore the interrelationships between data dimensions and key indicators, thereby providing a scientific basis for real-time decision-making (Ren,2022). Through the implementation of statistical analysis and machine learning methodologies, researchers can identify the pivotal factors influencing production efficiency and discern potential interdependencies among data elements. This methodological approach facilitates a comprehensive understanding of how disparate data dimensions interact with one another, thereby providing a foundational framework for optimizing resource allocation and enhancing production flexibility.

3.2 Smart Warehouses and Production Scheduling

3.2.1 Application of Mixed-Integer Programming Models in Scheduling Optimization

In the context of a Smart Warehouse environment, correlation analysis frequently entails the management of resources, including scheduling and allocation. For instance, alterations in equipment

status, process priorities, and material inventory can directly influence the execution of tasks on an assembly line. MIP is an optimization algorithm capable of handling models with both integer and continuous variables, making it highly suitable for addressing complex scheduling problems in smart warehouses, particularly those involving resource conflicts and priority allocation. MIP methods can represent these variables and their interdependencies as a set of mathematical constraints and an objective function. By optimizing these constraints, the algorithm attains a globally optimal schedule.

3.2.2 Model Definition

Within the MIP model, it is imperative to delineate the objective function and constraints.

The objective of optimization is to be established, and it may pertain to the minimization of production cycle time, inventory costs, or equipment utilization. In the context of intelligent warehouses, the objective is to enhance equipment utilization and resource dynamic adaptability by minimizing completion time and inventory costs. The parameters are defined as shown in Table 1 and Table 2.

Table 1: Core Parameter Table

Decision variables	Meaning
X_{ijt}	Indicates whether task j is assigned to device i at time t . If so, $X_{ijt}=1$; otherwise, $X_{ijt}=0$
S_{jt}	Indicates the start time of task j at time t
C_{jt}	Indicates the completion time of task j at time t
I_{kt}	Indicates the quantity of inventory material k at time t

Table 2: Core Parameter Table

Parameters	Meaning
T_{ij}	Processing time of task j on device i
M	A sufficiently large constant to ensure task order
D_j	Deadline for task j
P_k	Inventory cost per unit of material k
R_k	Material quantity required for task
K_i	Maximum processing capacity of device i

Objective function: Minimize the total completion time and inventory cost

$$\text{minimize } Z = \sum_j C_j + \sum_{k,t} P_k \cdot I_{kt} \quad (1)$$

where C_j is the completion time of task j , and $P_k \cdot I_{kt}$ is the inventory cost of each material in each time period.

Resource allocation constraint: Each task can only be assigned to one device.

$$\sum_i X_{ijt} = 1 \quad \forall j, t \quad (2)$$

Device capacity constraint: The task load of each device cannot exceed its processing capacity.

$$\sum_j X_{ijt} \leq K_i \quad \forall i, t \quad (3)$$

Task start and end time constraints:

$$S_{jt} + T_{ij} \cdot X_{ijt} \leq C_{jt} \quad \forall i, j, t \quad (4)$$

Process priority constraint: Task j can only start after task k is completed.

$$S_{jt} \geq C_{kt} + M \cdot (1 - X_{ijt}) \quad \forall i, j \neq k, t \quad (5)$$

Inventory update constraint: The inventory level at each time period is updated based on production and consumption.

$$I_{kt+1} = I_{kt} + \sum_j R_k \cdot X_{ijt} - D_j \quad \forall k, t \quad (6)$$

3.3 Model Results Analysis

3.3.1 Results Interpretation

Following the resolution of the model, a systematic analysis was conducted, with a focus on the specific task allocation and the operational status of the equipment associated with each task. A comparison of the model solution results with actual production data allows for an effective evaluation of the model's performance and its applicability in practical applications. This analysis suggests that managers can adjust their scheduling strategies promptly, thereby enhancing resource allocation efficiency.

Specifically, the MIP model optimized the allocation of equipment and tasks, thereby effectively reducing equipment idle time in a non-flow production mode. The model demonstrated a substantial enhancement in equipment utilization, leading to a notable reduction in resource waste stemming from equipment idling (Ni, 2022). This improvement was achieved through the dynamic allocation of tasks to the most appropriate equipment, thereby optimizing resource usage. Furthermore, the model meticulously scheduled the commencement

and conclusion of each production task, ensuring that tasks were executed by their relative priorities. This approach not only reduced waiting times within the production process but also enhanced the production system's capacity to adapt to evolving market demands. Consequently, this methodology contributed to a reduction in the overall production cycle and an improvement in delivery efficiency, Figure 3 shows the correlation analysis process.

In the context of material management, the MIP model can dynamically adjust real-time material demands and inventory status, thereby reducing inventory backlogs. The model can automatically identify and determine the optimal replenishment timing and quantity for materials. This capability effectively reduces unnecessary inventory costs and further optimizes material management (Huang, 2019). In the context of island production models, the implementation of the MIP model enables the system to achieve efficient coordination between production units, thereby avoiding resource conflicts and bottlenecks. This coordination mechanism has been demonstrated to enhance overall production efficiency while ensuring production flexibility.

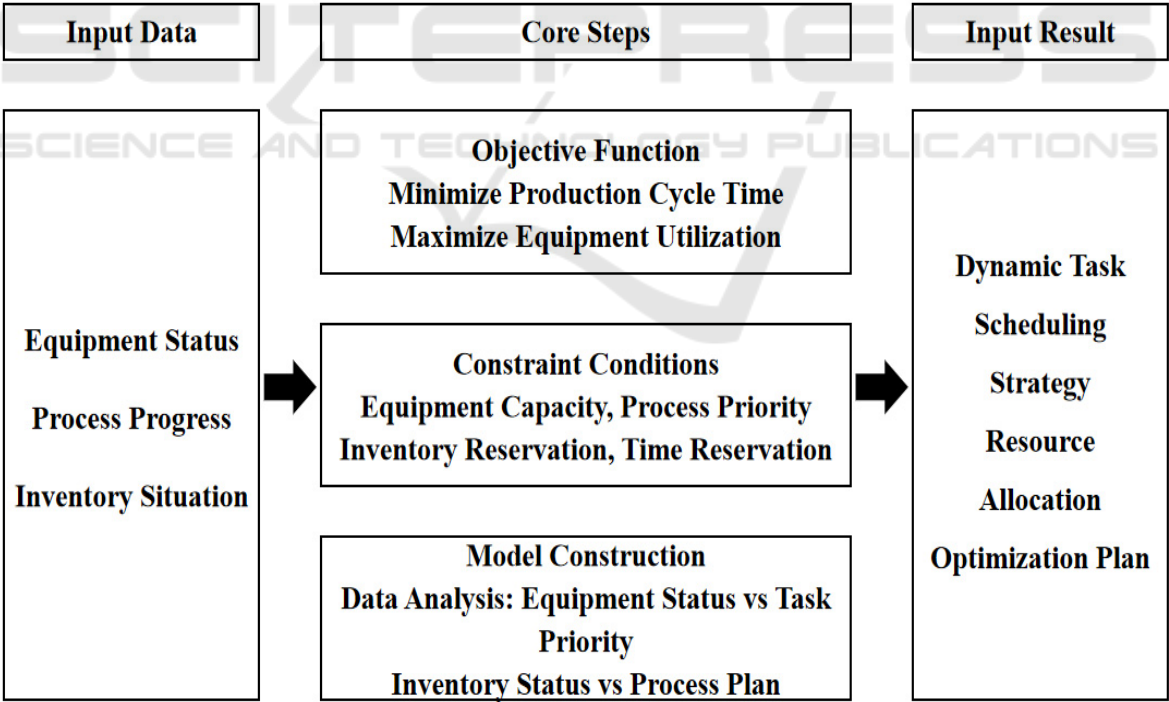


Figure 3: Correlation analysis process (Picture credit: Original)

3.3.2 Application Analysis

The MIP model exhibits considerable adaptability in responding to fluctuations in production demand, particularly in cases of variable order demand. The model's capacity for expeditious reallocation of resources is pivotal in ensuring the prioritized execution of critical tasks, a feature that is particularly salient in contexts characterized by the fulfillment of bespoke and limited production volumes. The model's scheduling optimization has been shown to improve the production system's responsiveness and adaptability to market changes, enhancing its flexibility and efficiency.

Furthermore, the MIP model provides accurate decision support by leveraging real-time data to optimize production planning and scheduling decisions. The integration of data analysis enables management to make more precise decisions, informed by real-time feedback. This approach effectively mitigates production deviations and reduces resource wastage, thereby enhancing overall production efficiency (Ren, 2022). This process exemplifies the merits of data empowerment in decision-making, thereby enhancing the scientific rigor and efficiency of production scheduling.

The MIP model has been demonstrated to play a dual role in terms of quality and cost improvement. The model's efficacy is demonstrated by its ability to optimize equipment utilization and inventory management, thereby reducing inventory costs while enhancing quality control levels. The model incorporates a priority allocation function for critical equipment and materials, thereby averting quality issues stemming from material shortages or equipment failures and ensuring effective cost control during production. This optimization not only ensures product quality but also further improves production economics.

The MIP model establishes a sustainable feedback optimization mechanism. The model provides data support for future scheduling optimization through continuous feedback on execution results, thereby forming a cycle of continuous improvement. The production management team can use this feedback to continuously adjust resource allocation plans, thereby improving the adaptability and scalability of the model. This mechanism enables the MIP model to continuously optimize in a dynamic production environment, providing enterprises with long-term production management advantages.

4 CONCLUSIONS

The primary conclusions of this study emphasize the substantial influence of data empowerment on numerous pivotal indicators within non-assembly line production models. Firstly, the enhancement in equipment utilization is indicative of the optimization of resource scheduling that is driven by data. The implementation of real-time data collection and intelligent task allocation is instrumental in enhancing the operational efficiency of production equipment. This, in turn, leads to a reduction in equipment idle time and ensures the optimal utilization of overall production capacity. Secondly, the enhancement in inventory turnover rate substantiates the efficacy of data empowerment in inventory management. Conventional inventory management is characterized by substantial expenses and protracted lead times. Conversely, data empowerment employs dynamic integration of production, inventory, and order data to optimize replenishment strategies and storage routes, thereby effectively mitigating inventory buildup and shortage risks. About the production cycle time, the empowerment of data results in a reduction of said cycle through the optimization of task allocation and resource configuration. Intelligent algorithms circumvent traditional production issues, such as process queuing and resource conflicts, by prioritizing processes and considering resource constraints. This renders the production process more efficient and seamless. Furthermore, the enhancement in process completion and task execution rates underscores the pivotal role of data empowerment in facilitating effective production coordination. The real-time dissemination of pivotal production data facilitates seamless coordination among processes, mitigates production delays, and enhances the stability of the production rhythm.

In summary, the application of data empowerment in non-assembly line production models can effectively improve key production indicators, optimize resource allocation, enhance production efficiency, and strengthen system flexibility and responsiveness. Enterprises can enhance their responsiveness to market demand changes and production environment uncertainties by leveraging accurate data analysis, intelligent scheduling, and resource optimization. This, in turn, can lead to improvements in overall competitiveness. Data empowerment has been shown to improve production efficiency and provide enterprises with more efficient decision-making support and operational capabilities in a dynamic market environment. Consequently, this

can drive the non-assembly line production model toward greater efficiency and flexibility.

The findings of this study offer novel insights for future research, particularly in the domains of production process optimization and intelligent scheduling. The findings suggest that data empowerment has a substantial impact on equipment utilization, inventory management, and production cycle acceleration. This prompts numerous avenues for future research, particularly about the enhancement of system intelligence, the augmentation of data accuracy and real-time performance, and the adaptation to more intricate and evolving production environments.

Subsequent research endeavors should concentrate on investigating methodologies for the dissemination of data-empowered technologies across diverse industry sectors, with a particular emphasis on those domains characterized by intricate resource scheduling and considerable demand fluctuations. Furthermore, cross-industry applications and system integration will be pivotal in the development of data-empowered technologies. Research must explore the profound integration of data technologies with conventional manufacturing industries and the innovative application of intelligent algorithms.

REFERENCES

- Chen, L., & Wu, M., 2021. Design of an intelligent workshop quality data integration and visualization analysis platform. *Computer-Integrated Manufacturing Systems*, 27(06), 1641-1649.
- Fang, W., Guo, Y., Huang, S., Liu, D., Cui, S., Liao, W., & Hong, D., 2021. Research on intelligent control methods for production processes in discrete manufacturing workshops driven by big data. *Transactions of the Chinese Society of Mechanical Engineering*, 57(20), 277-291.
- Huang, S., Guo, Y., Cha, S., Fang, W., & Wang, F., 2019. Research and application of IoT in discrete manufacturing workshops and its key technologies. *Computer-Integrated Manufacturing Systems*, 25(02), 284-302.
- Li, X., Tong, Y., & Cao, F., 2025. Enterprise digital transformation and participation in global value chains. *Journal of Management Engineering*, 39(01), 15-31.
- Ni, Y., Cai, G., Zhao, Y., & Wang, Z., 2022. A pricing model for a one-stop service platform for technology transactions under dual objectives and multiple stakeholders. *Journal of Industrial Engineering and Management*, 27(03), 24-32.
- Ren, L., Jia, Z., Lai, L., Zhou, L., Zhang, L., & Li, B., 2022. Data-driven industrial intelligence: Current status and

future prospects. *Computer-Integrated Manufacturing Systems*, 28(07), 1913-1939.

- Tang, J., Ren, Y., Yu, Y., & Han, Y., 2021. Comparison and simulation analysis of SERU production and classic production methods. *Nankai Management Review*, 24(02), 126-136.
- Wang, M., Wang, L., Xu, X., & Qin, Y., 2022. Real-time scheduling model for high-speed trains under severe initial delays and interval speed limits. *Journal of Railway Engineering*, 44(01), 8-16.
- Wu, L., & Zhen, L., 2025. Research on mathematical programming algorithms for optimizing production operations management. *Chinese Journal of Management Science*, 33(01), 345-355.
- Zhang, C., & You, M., 2022. A supply chain coordination model based on credit payment under retailers' fairness preferences. *Industrial Engineering and Management*, 27(03), 44-53.
- Zhang, M., & Zhao, H., 2024. A study on the mechanism of industrial internet empowering enterprise green development from a value chain perspective. *Science and Industry*, 24(06), 1-9.
- Zheng, S., & Sha, J., 2022. Research on container allocation and container handling coordination optimization considering synchronous entry and exit of containers. *Industrial Engineering and Management*, 27(03), 33-43.