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DEVELOPMENT OF VIRTUAL ASSEMBLY WORKSTATION SIMULATION FOR INDUSTRY 4.0

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Abstract

This article aims to explore the simulation research of Industry 4.0 virtual assembly workstations. The study first introduced the core concepts of Industry 4.0 and its important role in the manufacturing industry, with a particular emphasis on the crucial role of virtual simulation technology in achieving intelligent production processes. Subsequently, the paper elaborated on the functional characteristics of Factory IO simulation software and its application advantages in virtual assembly workstation simulation. This article uses Factory IO to construct a digital model of a virtual assembly workstation and simulates the operation process of a programmable logic controller through PLC-SIM. Through the integrated application of these two software, a high degree of simulation of the production process of the assembly workstation has been achieved, including equipment layout, material transmission, assembly operations, and other various links. The research results indicate that virtual assembly workstation simulation based on Factory IO and PLC-SIM can effectively simulate the actual production environment, providing strong support for optimizing production processes and improving production efficiency. This article summarizes the important significance of virtual simulation technology in the era of Industry 4.0. Through this study, we provide an effective solution for simulating virtual assembly workstations in Industry 4.0 and provide useful exploration and reference for the intelligent upgrading of the manufacturing industry.

Keywords: Factory IO, Industry 4.0, PLC-SIM, Virtual assembly.

1. Introduction

With the rapid advancement of technology, the industrial sector is undergoing a profound transformation led by Industry 4.0 [1]. This is not only a technological revolution, but also a leap in thinking, pushing traditional manufacturing to a new height [2]. The core of Industry 4.0 lies in the digital integration of the entire manufacturing process, supply chain, logistics and other aspects, achieving maximum data flow and information sharing [3]. This transformation not only enables enterprises to adapt to market dynamics more quickly, but also greatly improves production efficiency and product quality. Under the framework of Industry 4.0, intelligent manufacturing has become the core driving force [4].

With the help of advanced sensors, automation equipment, and data analysis technology, the production process can be made intelligent, not only improving production efficiency, but also significantly reducing human errors [5], making the manufacturing process more precise and reliable. In addition, the digital industry provides the possibility for personalized customization, allowing enterprises to gain insights into customer needs through data and customize products that meet individual needs, greatly improving customer satisfaction. In the context of Industry 4.0, digital and intelligent factories are gradually becoming the mainstream of industrial manufacturing [6]. 3D simulation technology, as an indispensable part of digital industry, will continue to play a crucial role in industrial automation. This article aims to explore Industry 4.0 and its impact and application prospects on digital industry, especially 3D simulation technology, in order to provide useful thinking and inspiration for sustained innovation and development in the industrial field [7].

In the wave of Industry 4.0, there are still many unanswered questions and research spaces on how to combine services, instruments, and material assembly systems to achieve autonomous and intelligent production, as well as how to effectively manage production processes and real-time data communication [8]. This study aims to provide new insights and practices in this field.

In order to achieve the practical application of 3D intelligent factories in the field of material assembly, this study combines Factory IO software and PLC-SIM. By simulating the key steps in the actual material assembly process, such as material production, handling, assembly, etc., this study created a virtual material assembly system. This system can not only help us visually identify bottlenecks and optimization points in the production process but also predict production efficiency and output [9].

This study proposes a series of suggestions to improve the efficiency and performance of material assembly systems, such as optimizing production processes, adjusting equipment layout, and enhancing automation levels [10].

To verify the effectiveness of these suggestions, a series of systematic evaluations were also conducted in this study, include testing and analysing the material assembly system with the aim of identifying potential issues and improvement points. The evaluation results not only verify the accuracy of the simulation system but also provide strong data support for subsequent improvement work. Meanwhile, optimizing the production cycle time is also of great significance for shortening customer delivery time and improving customer satisfaction.

In summary, this study provides useful exploration and practice for the intelligent upgrade of material assembly systems in the context of Industry 4.0. In the future, we can further expand the application of digital twin models in the field of material assembly, continuously optimize production processes and improve system performance through data analysis and simulation, providing strong support for achieving intelligent, efficient, and sustainable material assembly production.

2. Overview of the Related Work

2.1. The concept and composition of industry 4.0

Industry 4.0 refers to the integration of the real world and virtual networks, with information physical systems as the core and communication technology as the foundation. Forming a new era of technology that combines virtual and real in the field of industrial manufacturing. The goal of Industry 4.0 is to build intelligent, networked, flexible, and personalized manufacturing systems to meet diverse, high-quality, and low-cost market demands [11].

The main components of Industry 4.0 include the following aspects:

1) Intelligent products refer to products that have the ability to autonomously recognize, locate, perceive, interact, learn, and make decisions, and can adaptively adjust according to user needs and environmental changes.
2) Intelligent devices refer to devices with autonomous perception, control, optimization, coordination, and maintenance capabilities that can intelligently interact with other devices, products, and systems.
3) Intelligent factory refers to the use of technologies such as the Internet of Things, cloud computing, big data, and artificial intelligence to achieve information integration within and outside the factory, enabling real-time monitoring, simulation, optimization scheduling, and autonomous management of the production process.
4) Intelligent services refer to intelligent services based on digital twin technology, providing full lifecycle services from product design, production and manufacturing, logistics distribution, use and maintenance to recycling and reuse, improving product added value and customer satisfaction.

Digital twin technology is one of the key technologies in Industry 4.0. By combining real physical foundations with virtual technology and monitoring virtual models, comprehensive monitoring and simulation of the production process can be achieved, thereby improving production efficiency, reducing costs, and improving product quality. Digital twin technology has been widely applied in various fields of manufacturing, such as intelligent machine tools, intelligent factories, intelligent logistics, and intelligent services.

2.2. Smart factory and digital twin

In today's highly informative era, the combination of intelligent factories and digital twins is gradually becoming a new trend in the development of manufacturing industry [12]. As an important product of modern manufacturing, intelligent factories achieve automation and intelligence in production processes by integrating advanced Internet of Things technology, big data analysis, cloud computing, and more. As a product of the integration of digital technology and the physical world, digital twins provide a new perspective and method for the production management of intelligent factories.

Intelligent factories achieve real-time monitoring and precise control of the production process through digital twin technology. Digital twin technology builds a virtual production environment and maps real-time production data from the real world to virtual models, enabling managers to have a more intuitive understanding of production status, timely identify potential problems, and carry out targeted optimization and improvement [13].

Digital twin technology provides powerful data support for the production management of intelligent factories. Through big data analysis, managers can gain a deeper understanding of various patterns in the production process, predict future production trends, and develop more scientific and reasonable production plans. This can not only improve production efficiency, but also effectively avoid resource waste.

The combination of smart factories and digital twins helps to improve product quality and reliability. By monitoring various parameters in real-time during the production process, managers can promptly detect abnormalities in the production process and make timely adjustments and treatments. This can not only ensure the quality of the product but also improve its reliability and enhance the market competitiveness of the enterprise.

The application of smart factories and digital twins helps drive the digital transformation of enterprises. With the continuous development of digital technology, the combination of intelligent factories and digital twins will become an important direction for the transformation and upgrading of the manufacturing industry. Through digital transformation, enterprises can more efficiently integrate resources, improve production efficiency, reduce costs, and achieve sustainable development.

The combination of intelligent factories and digital twins is of great significance for the development of modern manufacturing industry. Through real-time monitoring, precise control, data support, and digital transformation, smart factories and digital twins will bring more efficient, intelligent, and sustainable production methods to enterprises, promoting the transformation and upgrading of the manufacturing industry.

3. Methodology and Approach

3.1. Production and processing centre

The first production centre on the top left as shown in Fig. 1 is responsible for producing lids, while the second production centre on the top right is responsible for producing bases. Both production and processing centres produce grey, blue, and green raw materials. When the start button of the control cabinet is pressed, the raw material launch device transfers the raw materials to the processing centre for processing and production. After production is completed, the processing centre places the materials at the outlet. At this time, the outlet sensor detects the materials, and the conveyor belt transfers the materials to the next station. A simulated view of the machining centre is shown in Fig. 2.

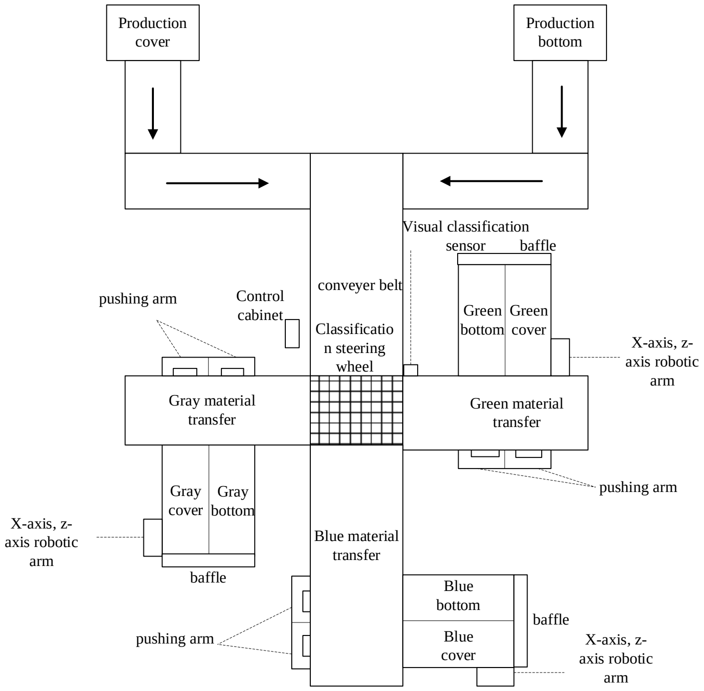


Fig. 1. Overall design block diagram of the system.

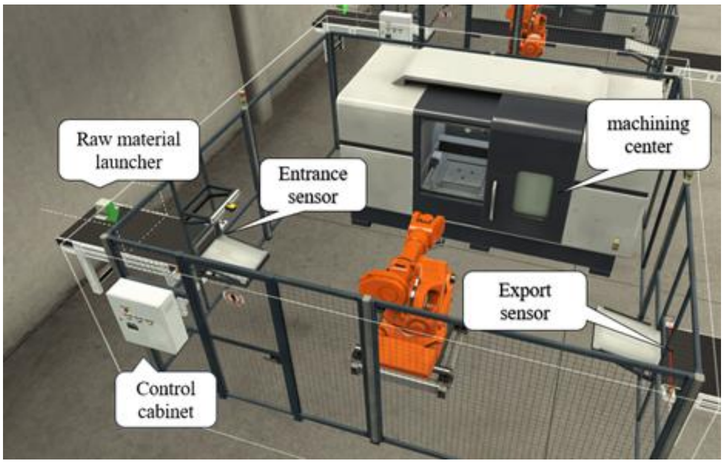


Fig. 2. Machining centre 3D simulation view with labels.

3.2. Material classification

Material classification consists of visual sensors, classifiers, material push arms, collection devices, and other essential parts, as shown in Fig. 3. When the conveyor belt transfers the corresponding grey lids, bases, blue lids, bases, and green lids and bases to the visual sensor, different types of items are classified into different channels based on the set corresponding information classifier. The corresponding parameters for the visual sensor to recognize items are shown in Table 1.

Table 1. Visual sensor output values.

Material	Sensor Output Values
Gray Cover	8
Gray Base	9
Blue Cover	2
Blue Base	3
Green Cover	5
Green Base	6

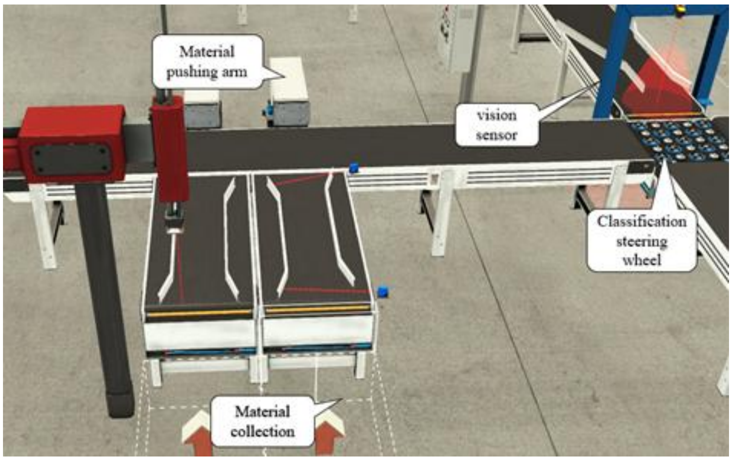


Fig. 3. Classification centre 3D simulation view with labels.

If the visual sensor recognizes the material as grey, and the classifier rotates to the left. Then, the roller continues to move and sends the material to the right conveyor belt; If it is a blue material, the classifier roller will operate normally; Green indicates a right turn. At this point, based on the recognition of the visual sensor, the material pushing arm can be classified accordingly. When the base enters the corresponding conveyor belt, the entrance sensor recognizes it, with the purpose of adjusting the working status of the installation robot arm. When there is a base, the corresponding robot arm can start to move to prevent equipment mis-operation.

3.3. Material assembly

The material assembly module consists of a conveyor belt, photoelectric sensors, robotic arms, fixing devices, control cabinets, and many more. Two buttons were installed in a distribution cabinet in the assembly centre. When there is a problem during the equipment process, such as excessive accumulation of the same material, press the collection button. At this time, the equipment enters the material collection state, allowing excess material to be collected; Press the run button to put the device into normal operation.

When the sensor on the robotic arm detects the arrival of materials, the baffle fixes the material cover and base. When the sensor determines that there are materials on both conveyor belts, the robotic arm starts to grab the cover and install it on the base. After assembly is completed, the bottom baffle descends, and the assembled materials are transported to the collection device.

3.4. Model design

Factory IO has a built-in scene editor that allows you to select desired workpieces from the parts library, such as conveyor belts, sensors, push arms, etc. After the model is built, it needs to communicate with PLC-SIM. The steps are as follows:

1) Firstly, edit the scene and call relevant conveyor belts, sensor production and processing centres, etc. according to the requirements to form the required factory model.
2) To communicate with Factory IO software through S7-PLCSIM, a communication protocol is required. Here, the engineering template provided by Factory IO needs to be used to communicate with Botong software PLC-SIM. After successful communication, the address in the configuration model is connected to the corresponding PLC's IO port.
3) By aligning the variable address with the corresponding variable address in TIAPortal16 and setting it correctly, Factory IO can communicate normally with PLC-SIM to achieve joint simulation.
4) Two processing and production centres are equipped with raw material launchers, which can be configured with material types, launch time interval parameters, etc. When conducting classification experiments, the material emitters are configured with three types of materials: grey, blue, and green, for production and transportation.
5) There are three types of classifier attributes: left turn, straight turn, and right turn. The classifier can be selected based on the actual model construction method and can perform forward and reverse turns. In this model, only the classifier needs to be turned forward.
6) Visual sensors classify materials of different colours and need to implement corresponding functions in the program.

The assembly experiment requires two inlet materials of the same colour. After the materials are classified, they will enter different conveyor belts. If there are materials on the grey, blue, green bottom and grey, blue, and green colour cover conveyor belts, the mechanical arm will perform the assembly action. The assembly process diagram is shown in Fig. 4.

3.5. Material assembly

Upon pressing the Factory IO start button, the raw material transmitter emits the raw material, and the inlet detects the raw material. Start the production robotic arm to grab the raw material for production, and the feeding conveyor belt stops. At the end of production, the robotic arm places the material at the outlet, and the outlet conveyor belt starts. The production centre is idle, and the feeding conveyor belt is started to continue the next round of production, as shown in Figs 5(a) and (b).

When using a visual sensor, a wheeled classifier is activated based on its value to achieve the first classification based on colour; Activate the classification push arm based on the values of the visual sensor to achieve classification of the cover and bottom. When the material reaches the bottom and the sensor detects it, the conveyor belt stops. If there is a base and cover on the conveyor belt, the mechanical arm is activated to sequentially move the X-axis and Z-axis to grab the cover and assemble it. The three colours of packaging are shown in Figs 5(c), (d), and (e). The actions of each component of the virtual model are connected to the PLC, and some variable allocation tables are shown in Table 2.

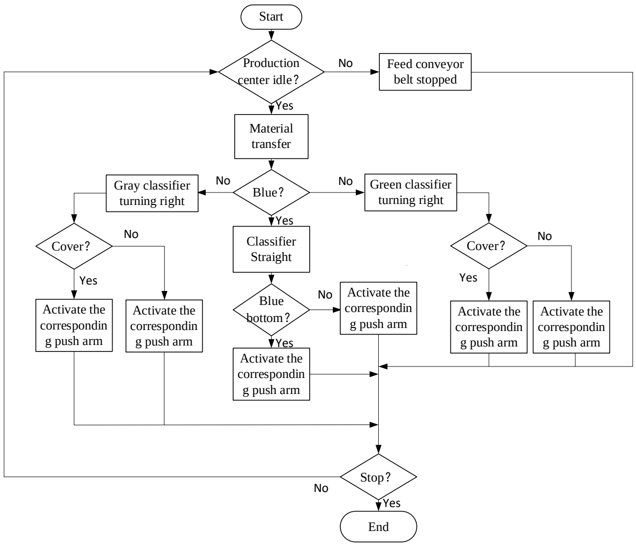


Fig. 4. Workflow diagram of the designed plant.

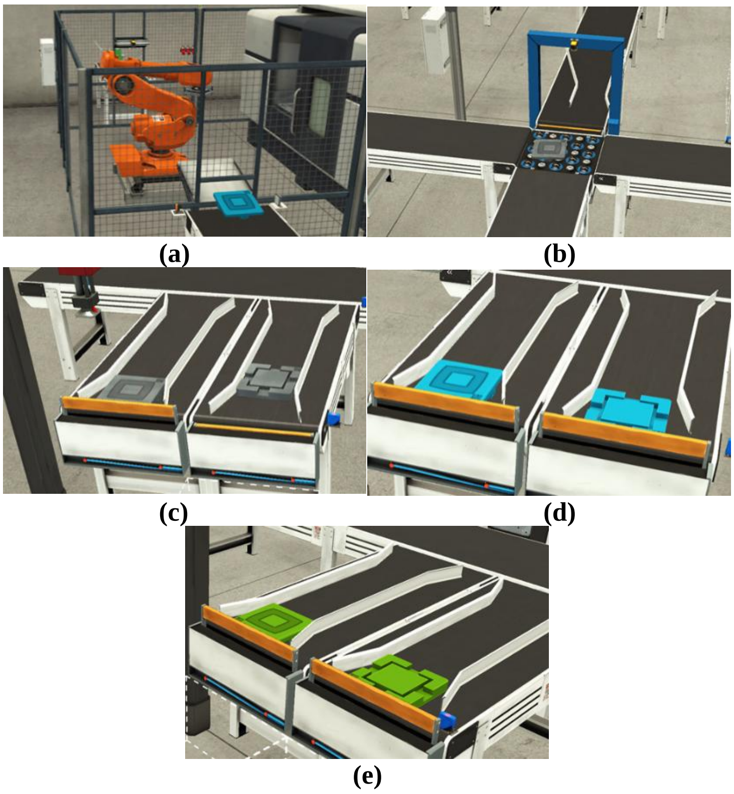


Fig. 5. 3D rendering and simulation of each step.

Table 2. PLC variable table.

Action	PLC variables	Action	PLC variables
Production Center 1 Raw Material Launcher	Q0.1	Mechanical arm 3 suction cup	Q3.3
Production Center 2 Raw Material Launcher	Q0.2	Robot arm 3X axis action	Q3.4
Production and processing centre 1 started	Q0.5	Robot arm 3Z axis action	Q3.5
Production and processing centre 2 started	Q0.6	Gray suction cup	Q3.6
Production Center 1 Entrance Conveyor Belt	Q1.0	Classification push arm grey base	Q1.5
Production Center 2 Entrance Conveyor Belt	Q1.1	Classification push arm blue cover	Q1.6
Wheel steering - left turn	Q4.0	Classification push arm blue base	Q1.7
Wheel steering - right turn	Q4.1	Classification push arm green cover	Q2.0
Wheel steering - forward rotation	Q4.2	Classification push arm green base	Q2.1
Mechanical arm 1 suction cup	Q2.5	Green cover and baffle	Q5.2
Robot arm 1X axis action	Q2.6	vision sensor	ID30
Robot arm 1Z axis action	Q2.7	Gray bottom inlet sensor	I1.0
Mechanical arm 2 suction cup	Q3.0	Gray left position sensor	I0.7
Robot arm 2X axis action	Q3.1	Green bottom in place sensor	I1.4
Robot arm 2Z axis action	Q3.2	Blue bottom inlet sensor	I1.5

4. Results and Discussion

The main role of Industry 4.0 is to combine mass production and customization. Therefore, in the current customized virtual assembly workstation system, productivity is a key performance indicator. This experiment will count the time of the 100 components produced.

$$T_t = T_s + T_y + T_a + T_d \quad (1)$$

where T_t: Total production time, T_s: Production and processing time, T_a: Transportation time, and T_d: Waiting time. We then have productivity,

$$R_t = \frac{60}{T_t} \quad (2)$$

Based on the simulation process of Factory IO, the material production process was observed, and the production of 100 materials was calculated as a case study. In addition, the time for material production and processing is assumed to be equal. For example, the production and processing time for covers and bases in gray, green, and blue colors is 55 seconds, as shown in Table 3.

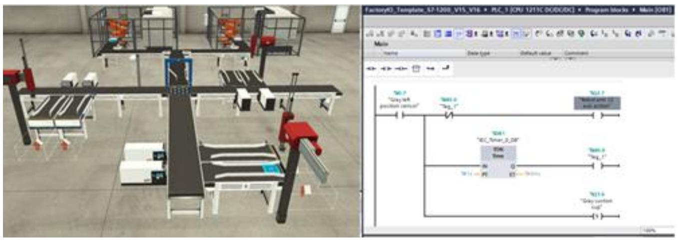
Table 3. PLC variable table.

Colour	Gray	Green	Blue
Number (pcs)	46	22	32
Average production and processing time (sec)	55	55	55
Average transportation time (sec)	21.2	18.4	19.2
average waiting time (sec)	25	63	42
Productivity (R_t)	101.4	136.2	116.4

Simulation analysis shows that due to slight differences in the length of the conveyor belt, it can be seen that there are differences in the average transportation time of each material. Although the simulation scenario produces green products with higher productivity, due to the randomness of production, the number of green products is relatively small, resulting in shorter waiting times; But the overall simulation results were smooth. When using simulation and software applications (i.e. Botu software and Factory IO), potential improvements can be identified before actual implementation by integrating IR4.0 enabling technologies such as simulation based modeling compared to physical models. Another potential improvement is to identify the sites affected by the fault as early as possible. This is one of the potential improvements related to maintenance.

Therefore, use TIA Protal and all variables in PLC-SIM and factory IO to ensure that the later simulation can correspond to the actual scene. A 3D production line model has been developed in the factory IO program to make supervision easier. Can track finished products and record faults. The clear image of the final 3D simulation factory is shown in Fig. 6. It can be seen that these two software programs are synchronized and the system is running normally.

In this study, in order to determine whether the system can operate accurately and stably, 9 sets of data were measured, each producing 100 materials for recording. Collecting data is to understand the stability, intelligence, efficiency, and sustainability of the system. This provides useful exploration and practice for future research on the intelligent upgrading of material assembly systems in the context of Industry 4.0. Average productivity statistics as shown in Table 4.



(a) (b)

Fig. 6. (a) Overview of the 3D rendering and simulation; (b) Run block diagram coded for the simulation.

Table 4. Average productivity statistics.

Tests	Grey material production	Green material production	Blue material production
1	108.5	116.2	115.8
2	122.2	113.3	121.6
3	144.3	118.5	115.0
4	114.9	119.8	116.2
5	117.4	120.2	119.3
6	132.1	117.9	117.5
7	130.7	141.4	119.2
8	110.8	119.5	118.3
9	119.1	118.6	117.7
Average	**122.8**	**117.4**	**118.9**

5. Conclusions

When factories meet their internal needs, they need to conduct system simulation and functional testing in advance. Good test results can have a significant impact on the current costs and revenue generated by the company. As part of this study, in order to implement the concept of Industry 4.0, a virtual assembly workstation simulation for Industry 4.0 was developed. In addition, the assembly of materials has been successfully achieved, and through testing, the logic has been made feasible.

The combination of PLC-SIM and Factory IO is used to calculate and simulate the possible results of the designed virtual assembly workstation. The ladder diagram aims to track and predict faults. Based on simulation results, an interactive mode for step-by-step inspection of the operational processes is proposed in this paper. Synchronizing these two software systems can better predict, identify system faults, and accurately locate fault locations. In addition, through the software's ability to simulate the layout of a visual factory, the performance and configuration of the system can be analyzed more easily and quickly based on customer changes.

According to the simulation results, it can be seen that the simulation efficiency is high and the success rate is high, which proves the effectiveness and efficiency of digital twin modelling. In addition, by analysing the digital twin model, it is possible to effectively understand the specific problems encountered during actual production and transportation, and to systematically diagnose the performance of the assembly workstation system. For example, the proposed simulation system can predict fault problems such as sorting and assembly, and can change programming logic, sensor positions, and factory structure in real time.

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