Optimization Method for Digital Twin Manufacturing System Based on NSGA-II

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***Abstract*—In the wave of industrial modernization, a concept that comprehensively covers the product lifecycle has been proposed, namely the digital twin manufacturing system. The digital twin manufacturing system can conduct three-dimensional simulation of the workshop, thereby achieving dynamic scheduling and energy efficiency optimization of the workshop. The optimization of digital twin manufacturing systems has become a focus of research. In order to reduce power consumption and production time in manufacturing workshops, the study adopted a non-dominated sorting genetic algorithm to improve its elitist retention strategy for the problem of easily falling into local optima. On the ground of the idea of multi-objective optimization, the optimization was carried out with the production time and power consumption of the manufacturing industry as the objectives. The experiment showcased that the improved algorithm outperforms the multi-objective optimization algorithm on the ground of decomposition and the evolutionary algorithm on the ground of Pareto dominance. Compared to the two comparison algorithms, the production time optimization effect and power consumption optimization effect of different numbers of devices were 11.12%-21.37% and 2.14%-6.89% higher, respectively. The optimization time of the improved algorithm was 713.5 seconds, that was reduced by 173.8 seconds and 179.8 seconds compared to the other two algorithms, respectively. The total power consumption of the improved optimization model was 2883.7kWs, which was reduced by 32.0kW*s and 45.5kW*s compared to the other two algorithms, respectively. This study proposed a new multi-objective optimization algorithm for the current digital twin manufacturing industry. This algorithm effectively reduces production time and power consumption, and has important guiding significance for manufacturing system optimization in actual production environments.**

Keywords—Multi-objective optimization; NSGA-II; Digital twin; Production time; Production energy consumption

I. Introduction

At present, China is entering a stage of high-quality development, and manufacturing, as one of the important core industries for achieving socialist modernization, is an important guarantee of comprehensive national strength. In traditional manufacturing models, product design, manufacturing, and service are usually isolated. This model is difficult to meet the personalized, intelligent, and environmentally friendly requirements of the current manufacturing industry [1]. The proposal of the Digital Twin Manufacturing System (DTMS) provides new ideas for solving these problems [2]. The DTMS comprehensively manages and controls all stages of the product from design to lifecycle through simulation and optimization. This can improve product quality and production efficiency, and reduce production costs [3]. Modern industrial practice has shown that DTMSs can effectively change the production mode of the manufacturing industry, making it more intelligent and personalized [4]. However, how to optimize the construction and operation of DTMSs, improve their performance and efficiency, is an important research topic at present. This practice has proven that the application of optimization algorithms can effectively improve the performance and efficiency of DTMSs [5]. In view of this, in order to reduce power consumption and production time in manufacturing workshops, this study will explore the optimization and construction methods of DTMSs from both theoretical and methodological perspectives. Firstly, a DTMS optimization model on the ground of the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) will be constructed using existing optimization algorithms for reference. On this basis, through in-depth research and improvement of the model, its performance and efficiency in practical applications are improved. The study improved the elite retention strategy of the NSGA-II algorithm, which requires retaining a portion of non-fully optimal solutions in addition to retaining elite individuals. The significance of this improvement is to avoid local convergence of the results and improve the accuracy of the calculation results for multi-objective optimization problems. The innovation of this study lies in the idea of flexible scheduling on the ground of flexible workshops, combined with digital twin technology, to construct an optimization model for green manufacturing industry. It effectively improves the practicality and availability of optimization strategies. Through this research, not only can the performance and efficiency of DTMSs be improved, but it can also promote technological progress and industry transformation in the manufacturing industry. The contribution of this study lies not only in constructing an effective optimization model for DTMSs, but also in providing new theories and methods for further research and application of DTMSs. This will have a profound impact on the development of the manufacturing industry and will also have a positive driving effect on the development of the social economy. The research is divided into five sections. Section II is a summary of the research related fields, namely DTMSs and industrial optimization, which involve the application of digital twin technology in the manufacturing industry and the application of algorithms in improving production efficiency in the manufacturing industry. Section III is the implementation of the method proposed by the research institute, which involves the construction of digital twin green models and multi-objective optimization models for the manufacturing industry. Section IV is the validation of the method proposed by the research institute, which includes iterative performance, convergence performance, time optimization performance, and energy consumption optimization performance. Section V is a summary and outlook of the research.

II. Related Works

DTMS is an emerging manufacturing system model that integrates physical and virtual manufacturing systems in real-time, dynamic, and highly consistent manner throughout their entire lifecycle. It is on the ground of advanced technologies such as the Internet of Things, cloud computing, and big data, and establishes a virtual image of a physical manufacturing system by collecting various data from the manufacturing system. Then, through continuous learning and model updates, the virtual image can reflect the state of the physical system in real time. Liu et al. proposed a real-time collaborative method on the ground of digital twin technology to address the treatment and efficiency issues in the production of new products. This method utilized heterogeneous information network modeling for real-time analysis and optimization of product production processes, and experimental results verified the feasibility and practicality of this method [6]. Guo et al. introduced a manufacturing logistics integration technology on the ground of digital twin technology to address the synchronization issue of manufacturing logistics interfaces in the production manufacturing industry, and established an equivalent constraint programming model to verify this. The experiment showcased that this method effectively achieves synchronization between logistics and manufacturing industries [7]. Fan et al. proposed a manufacturing structure on the ground of the digital twin scenario system in response to the development trend of Industry 4.0. The experiment showcased that this method is very effective at every stage of the product lifecycle [8]. Chetan et al. proposed a high-fidelity digital twin wind turbine blade virtual model to generate accurate blade models. This model improved the accuracy of the model by incorporating progressive calibration, and experimental results demonstrated the effectiveness and practicality of this method [9]. Osho proposed a modular digital twin framework to enhance its applicability in the manufacturing industry to enhance its applicability. The experimental results have proven the accuracy of this method in practice, laying a solid foundation for the further application of digital twin technology in the manufacturing industry [10].

Industrial manufacturing optimization refers to achieving more efficient and sustainable industrial manufacturing by improving and optimizing production processes, improving production efficiency, reducing costs and resource consumption, and other means. Using computer algorithms to optimize industrial manufacturing can achieve multi-objective optimization while also achieving intelligence and automation in the industrial manufacturing process. By learning and analyzing data, algorithms can continuously optimize the production process, improve production efficiency and quality. Singh et al. proposed an optimization strategy for the trajectory of industrial robotic arms on the ground of a hybrid optimization algorithm. The joint trajectory was optimized using a seventh order polynomial function. The experiment showcased that this method effectively improves the smoothness and efficiency of the robot [11]. Wu et al. analyzed the manufacturing economy in the post pandemic era in the region on the ground of a dual sector economic growth model, combined with descriptive statistics and grey correlation method. And it has put forward suggestions for optimizing the industrial structure of the manufacturing industry on the ground of the actual situation. This provided a reference for regional economic development and industrial structure optimization in the post pandemic era [12]. Sekaran et al. introduced a multi-objective opposition learning artificial ant colony optimization technique on the ground of directed acyclic graph theory to improve the communication cost of physical systems in IoT networks and the production efficiency of production lines. This was to optimize complex processes in industrial manufacturing. The experiment showcased that this method reduces production costs with minimal latency and computational overhead [13]. Chen et al. proposed a manufacturing optimization technology on the ground of container deployment model, which saved bandwidth resources and improves production efficiency by reducing communication latency. The experiment showcased that this method is highly effective in optimizing resource utilization and reducing deployment costs [14]. Morse et al. proposed a structural optimization method on the ground of boundary element method to improve structural stability in the aircraft manufacturing industry, and considered manufacturing costs. The experiment showcased that this method achieves full shape optimization of aircraft panel structures and has extremely high efficiency [15].

In summary, DTMSs are currently the focus of industrial optimization problems. And computer algorithms have been widely applied in the optimization research of industrial manufacturing systems. After reviewing a large number of literatures, it can be concluded that computer algorithms make important contributions to manufacturing system optimization, especially in improving manufacturing efficiency, reducing costs, and improving product quality. However, there are still some shortcomings in current research, such as the stability and robustness of optimization methods that require further research and improvement. For these problems, considering the advantages that NSGA-II algorithm can take into account multiple complex and often conflicting manufacturing objectives, a digital twin manufacturing optimization strategy based on NSGA-II is proposed. NSGA-II maintains the diversity of solutions through fast non-dominated sorting and congestion distance calculation. This approach makes more efficient use of the real-time data provided by digital twin technology. At the same time, the digital twin technology can effectively support the iteration and evolution of the NSGA-II algorithm, so that each optimization of the manufacturing process is based on the latest and most accurate system data, ensuring that the optimization results are highly practical and accurate. Therefore, the research chooses to combine NSGA-II algorithm with digital twin manufacturing. This is to improve decision quality and production efficiency in manufacturing process.

III. Construction and Improvement of NSGA-II for Digital Twin Manufacturing Industry

Considering the characteristics of DTMSs, the main challenge faced by the construction of NSGA-II is multi-objective optimization problem [16]. In the construction of the NSGA-II, the data-driven characteristics of the DTMS and its parallel processing ability in complex manufacturing processes are fully utilized. On the basis of algorithm construction, the optimization problem of NSGA-II was further explored. The selection, crossover, and mutation operations of algorithms have been thoroughly studied. The goal of this process is to find strategies and methods that can improve the efficiency and effectiveness of algorithms in dealing with large-scale parallel manufacturing system problems. To maintain the diversity of the population, new strategies were introduced in the optimization process. These strategies can maintain the diversity of the population during the optimization process, avoiding premature convergence and falling into local optima. The introduction of this strategy enables the algorithm to better balance the quality of solutions and the time required to solve practical problems.

A. *Construction of a Manufacturing System Considering Digital Twins*

In order to reduce the power consumption and production time of manufacturing workshops, a three-dimensional simulation of the workshop was conducted using a digital twin manufacturing system. A green model of manufacturing digital twins was constructed, and the energy consumption of the workshop was analyzed, providing direction and ideas for the subsequent optimization model construction. Afterwards, a multi-objective optimization model was constructed with power consumption and production time as optimization objectives, and the improved NSGA-II algorithm was used to solve the multi-objective problem. The scarcity of global resources and the increasing severity of environmental problems have forced industrial enterprises to use resources more efficiently and reduce their impact on the environment [17]. With the increasing demand for sustainable development in society, industrial enterprises need to take measures to reduce carbon emissions and waste emissions to achieve green and sustainable development. The digital twin green model can help industry achieve this goal. It is on the ground of digital twin technology and achieves real-time monitoring, optimization, and prediction of factories by modeling and simulating the physical systems of actual factories. This is to achieve the goals of efficient resource utilization, environmental friendliness, and economic sustainability [18]. Through digital twin technology, real-time monitoring of factory operations, energy consumption, waste generation, and other data can be achieved. And they were able to optimize on the ground of modeling and simulation. The schematic diagram of the manufacturing digital twin green model is shown in Fig. 1.

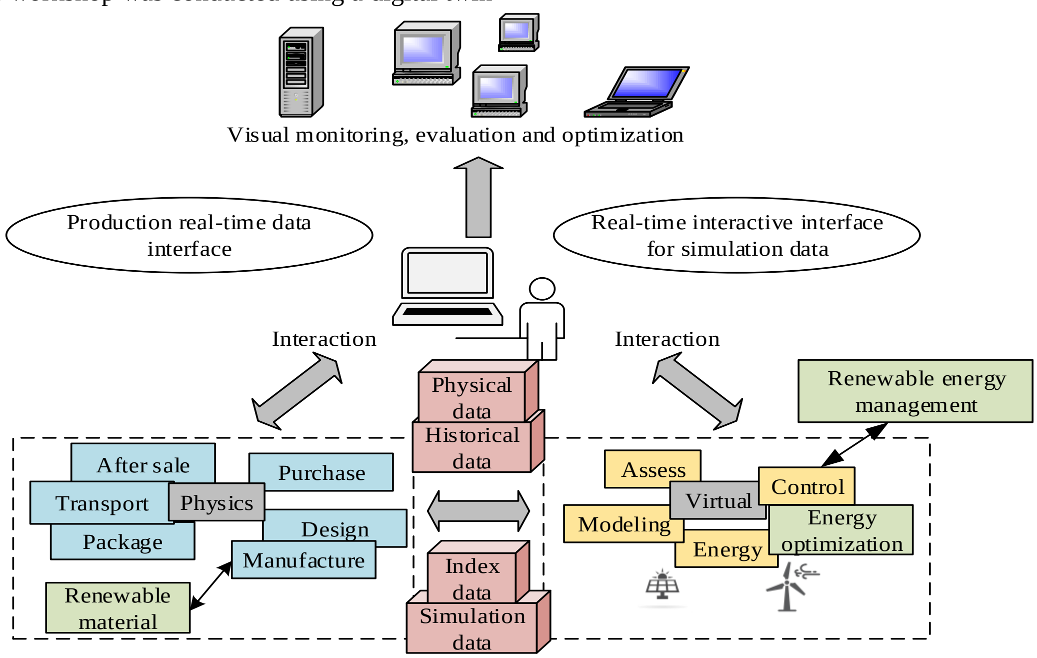

Fig. 1. Digital twin manufacturing green model.

Fig. 1 is a schematic diagram of the digital twin green model in the manufacturing industry. It forms a five dimensional model through the interaction between manufacturing entities, virtual entities, industrial data, services, and all elements. It can adjust the industry on the ground of real-time data to maximize production efficiency and costs while achieving multi-objective optimization. In digital twin technology, the core idea is to build a virtual model that reflects reality through continuous analysis of real-time data. Through the virtual model, the simulation, monitoring and optimization of the real factory can be realized in virtual. The most significant advantage is the ability to test optimizations, predict potential problems, and make production-related decisions in advance without interfering with actual production. The use of digital twin technology can effectively reduce production risks and improve efficiency. In the automotive industry, for example, in the design phase, the digital twin system is first used to test the automobile manufacturing to ensure the safety and feasibility of the process. In the manufacturing stage, the optimization of the manufacturing process is realized through the virtual planning and simulation of the production line. Then, in the test phase, the digital twin technology is used to carry out durability virtual collision and simulation. In the product sales phase, real-time data is used to assist inventory management and production adjustments are made based on real-time feedback. Digital twins can also guide the recovery and remanufacturing of vehicle products after they have reached the end of their life. Through the application of digital twin technology, the production efficiency and environmental friendliness of the bicycle manufacturing industry can be effectively improved. Formula (1) is a digital twin green energy consumption model.

$$M_{DT-GT} = \{P_g, V_g, D_g, S_g, C_g\} \tag{1}$$

In Formula (1), P_g represents the total physical energy consumption in the manufacturing workshop under energy consumption analysis. V_g represents a digital twin, whose main significance is to optimize energy consumption. D_g represents the overall data of the workshop, which is the connecting link with the digital twin. S_g represents optimization of energy consumption. C_g represents the interaction between real data and virtual data. As shown in Fig. 2, taking workshop work in the manufacturing industry as an example, it is optimized. On the ground of its energy consumption, this study continues to optimize and analyze it. On the ground of the basic energy consumption of the workshop, this study combines intelligent optimization algorithms. Then, on the ground of the actual situation, it constructs a green optimization and energy-saving operation strategy for workshop equipment, ultimately achieving optimization of workshop energy consumption. This can also reduce energy consumption and improve production efficiency.

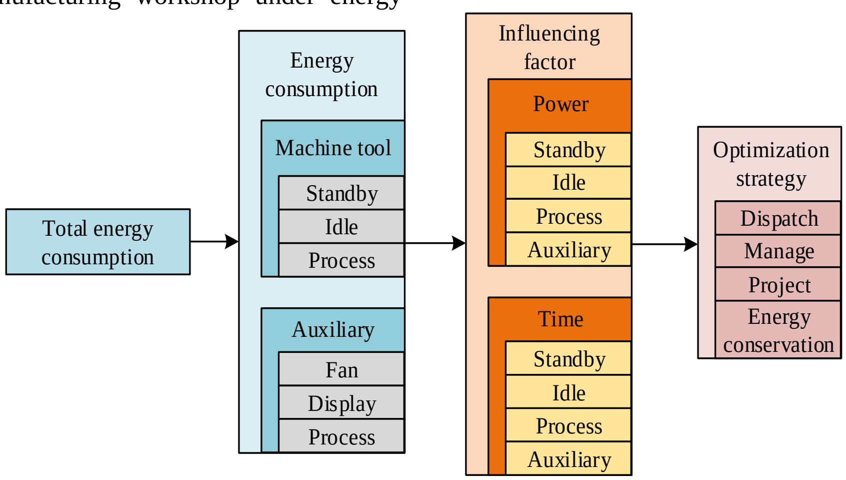

Fig. 2. Correlation analysis diagram of energy consumption, power and optimization of workshop.

Fig. 2 shows the key components of energy consumption analysis using workshop work in the manufacturing industry as an example. This includes machine tool energy consumption and auxiliary equipment energy consumption, and takes into account power consumption and time factors to plan better workshop optimization strategies. The power consumption model between machine speed and material removal rate can be expressed as shown in Formula (2).

$$P_1 = P_2 + k_1 n + b + k_0 MRR \tag{2}$$

In Formula (2), P_1 represents the total energy consumption in material removal. P_2 represents the total standby consumption, b represents the total fixed energy consumption of the device, n represents the speed unit of the device, k_1 represents the parameter setting of the spindle motor, k_0 represents a constant in the calculation, and MRR represents the material removal rate. Further consideration should be given to the power consumption of workshop machine tools. In the standby state of the equipment, the control system of the lathe remains in standby state, and the total standby power can be expressed as shown in formula (3).

$$P_s = P_c + P_l \tag{3}$$

In Formula (3), P_s represents standby power, P_c represents the system operating power of the workshop machine tool, which plays a major role in monitoring the entire system, and P_l represents the auxiliary equipment power. In the normal working state of the workshop, the power can be expressed as shown in Formula (4).

$$P_{Id} = P_s + P_{sf} \tag{4}$$

In Formula (4), P_{Id} represents the preparation power of the processing state, P_s represents the standby power, and P_{sf} represents the idle power of the spindle and the no-load power of the feed shaft. In the processing stage of the lathe, the main calculation required is the cutting power of the machine tool on the workpiece material, which can be expressed as shown in Formula (5).

$$P_w = P_s + P_{sf(n)} + P_m \tag{5}$$

In Formula (5), P_w represents the total power of the machining state, P_s represents the standby power, $P_{sf(n)}$ represents the power of the spindle and feed shaft in the working state, and P_m represents the cutting power of the material. Furthermore, according to the definition of integration, by integrating time over a period of time, the total power of the workshop machine tool can be calculated, as shown in Formula (6).

$$E_M = \int_0^{t_s} P_s d_t + \int_0^{t_{Id}} P_{Id} d_t + \int_0^{t_w} P_{Id} d_t \tag{6}$$

As shown in Formula (6), the total power of the workshop lathe during the processing stage can be calculated using the integration method, where t_s represents the standby time, t_{Id} represents the processing preparation time, and t_w represents the total processing time. As shown in Fig. 3, it is a schematic diagram of the process flow of a flexible workshop that adopts the optimization process method.

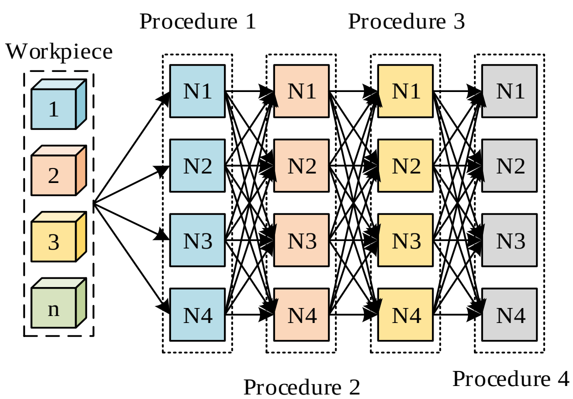

Fig. 3. Flexible workshop process flow diagram.

Fig. 3 is a schematic diagram of the flexible workshop process flow using optimized process methods, which can better align actual production needs with green concepts. Its main purpose is to reduce workshop production time while reducing equipment energy consumption, thereby achieving the concept of green manufacturing.

B. Construction and Optimization of NSGA-II for DTMSs

The characteristics of NSGA-II provide an effective solution for multi-objective problems in DTMSs. This algorithm achieves efficient search of high-quality solution sets through a non-sorted survival selection mechanism and crowding distance sorting [19]. However, integrating it into specific manufacturing environments requires a deep understanding of the characteristics of manufacturing systems to design optimization strategies that meet practical needs [20]. Firstly, it discusses the optimization scheduling objectives for the workshop. Overall, with manufacturing processing time as the main optimization objective, it can be represented by Formula (7).

$$\min T = \max\{C_1, C_2, \cdots, C_N\} \tag{7}$$

In Formula (7), $\min T$ represents the minimum optimized processing time, and $\{C_1, C_2, \cdots, C_N\}$ indicates different manufacturing system performance indicators. In the field of digital twin manufacturing, these indicators may represent key performance indicators such as production efficiency, resource consumption, environmental impact, etc. These indicators allow for optimization beyond a single objective, enabling the model to find the optimal solution in a larger dimensional space. In the whole optimization process, real-time optimization of the algorithm can be realized through real-time monitoring of these indicators, so as to dynamically adjust and optimize the manufacturing process. It further introduces the total power consumption of the workshop as the optimization scheduling objective. It can be specifically expressed as shown in Formula (8).

$$\min f = \min E_{total} \tag{8}$$

In Formula (8), $\min f$ represents the minimum objective function, and $\min E_{total}$ represents the minimum energy consumption optimization objective. The total workshop processing energy consumption can be expressed as shown in Formula (9).

$$E_{sum} = E_w + E_{IE} + E_A \tag{9}$$

In Formula (9), E_{sum} represents the total processing consumption, E_w represents the cutting power of the equipment, E_{IE} represents the idle standby power of the equipment, and E_A represents the additional loss power of the equipment. When processing each individual workpiece, a device needs to be selected for the processing process, which can be expressed in Formula (10).

$$\sum_{k=1}^{M_j} x_{ijk} = 1, (i = 1, 2, \cdots, w)(n - 1, 2, \cdots, s) \tag{10}$$

In Formula (10), M_j represents the number of machine tools required for the j-th process, $x_{ijk} = 1$. When $x_{ijk} = 1$, it indicates that the jth process of the i-th workpiece can be completed on the k-th machine tool, while $x_{ijk} = 0$ indicates that machining cannot be carried out. However, when the same machine tool is in operation, it is not possible to process two workpieces simultaneously. Therefore, as shown in Formula (11), it specifically represents the processing start and end times of the workpiece.

$$PF(j,k,r) \le PS(j,k,r+1) \tag{11}$$

In Formula (11), $PF(j,k,r)$ represents the processing end time of the jth process of the r-th workpiece on the k-th machine tool, and $PS(j,k,r+1)$ represents the processing start time of the jth process of the r+1 workpiece on the k-th machine tool. For each individual workpiece, it must be processed according to the processing process flow and must go through w processes to complete the processing. As shown in Formula (12).

$$\sum_{k=1}^{Mj} B_i^k = 1, \left(\forall i \in n, j \in s \right) \tag{12}$$

In Formula (12), M represents the number of devices that can be selected for use in the jth process of the workpiece, $B_i^k = 1$ indicates that workpiece i is processed on device K, and $B_i^k \neq 1$ indicates that workpiece i is not processed on device K. For multi-objective optimization problems, they can be represented as shown in Formula (13).

$$\begin{cases} \min\left(\&\max\right) F\left(x\right) = \left[f_1\left(x\right), f_2\left(x\right), \cdots, f_n\left(x\right) \right]^T \\ x \in \Omega \\ \Omega = \left\{ X \in R^n \middle| g_i\left(x\right) \le 0, i = 1, 2, \cdots, p \right\} \end{cases} \tag{13}$$

In Formula (13), the space Ω where X is located is the space where the feasible solution is located, while $F\left(x\right)$ represents the objective function of the space in which it is located. The core idea is to find the Pareto optimal solution. The NSGA-II, due to its strong anti-interference performance, performs well in finding the optimal solution for multi-objective optimization. The NSGA-II algorithm has difficulty in weighing different objectives, while Pareto optimization does not prioritize the optimization of a single objective. Instead, it seeks to find the best balance point among multiple objectives, aiming to identify solutions that improve one objective without significantly degrading the other. Pareto optimization can solve this problem in a targeted way, and at the same time, it also considers the global nature of the space, rather than limited to a specific target. Therefore, using Pareto optimization can also enhance the performance of NSGA-II in complex multi-objective optimization problems to a certain extent. Therefore, this algorithm was chosen for further research. The core idea of the NSGA-II is to use Pareto's sorting method in non-dominated space for solving. Pareto optimization can obtain a set of optimal solutions in the process and output them according to different levels, as shown in Fig. 4.

In Fig. 4, after selecting a more optimal solution, it is necessary to calculate the crowding degree. When the crowding distance is relatively large, the solution set around the optimal solution should appear more dispersed and sparse, to ensure the diversity of the population. Firstly, it assumes that the crowding degree of each point is n_d, and the initial crowding degree value is 0. For the optimal target point, by non-dominated sorting, it can be considered that the crowding degree of individual solutions on the boundary of the optimal solution is infinite. Finally, it calculates the crowding degree of other individuals within the population, as shown in Formula (14).

$$n_d = \sum_{j=1}^{m} \left(\left| f_j^{i+1} - f_j^{i-1} \right| \right) \tag{14}$$

In Formula (14), n_d represents crowding degree, f_j^{i+1} represents the function value of the j-th objective function at point $i+1$, f_j^{i-1} represents the function value of the j-th objective function at point $i-1$, and m represents the total number of functions, where $j \in 1, 2, \cdots, m$. For its elite strategy, the original NSGA-II, after Pareto optimization, would choose to retain as many outstanding individuals as possible and pass them on to the next generation. This strategy will to some extent reduce its genetic diversity, leading to local convergence after iteration. Therefore, the study optimizes its elite retention strategy. After Pareto optimization and congestion calculation, a portion of elite individuals are retained, and the remaining non-optimal individuals are uniformly selected for retention, as shown in Fig. 5.

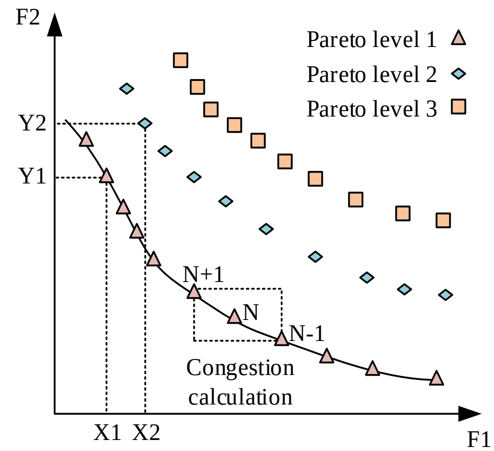

Fig. 4. Pareto optimization and congestion calculation diagram.

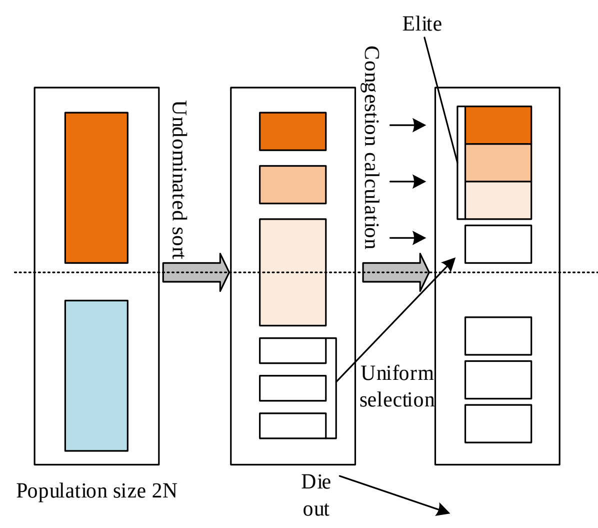

Fig. 5. Schematic diagram of optimizing elite retention strategy.

The NSGA-II has good performance in handling multi-objective optimization problems. However, to better adapt to the characteristics and needs of the digital twin manufacturing industry, its elite individual retention strategy has been optimized. On the basis of the original elite strategy, more selection criteria have been introduced to enhance diversity. Meanwhile, stricter control has been implemented on the quality of solutions to ensure the retention of high-quality solutions. The implementation of this optimization strategy aims to improve the search performance of the algorithm, so that a more optimal solution set can be found under the same number of iterations. In addition, this also helps to improve the stability of the algorithm and reduce the randomness of the running results. Moreover, due to the retention of elite individuals, it can to some extent avoid the loss of high-quality solutions, thereby effectively improving the performance of the algorithm. Furthermore, this optimization strategy makes it more suitable for optimizing the digital twin manufacturing industry. Because there are a large number of multi-objective optimization problems, which often require considering multiple factors to find the optimal solution set. For this type of problem, the NSGA-II, after optimization, can better meet its solving needs, thereby improving the efficiency and effectiveness of the manufacturing system. The flowchart of the NSGA-II is shown in Fig. 6.

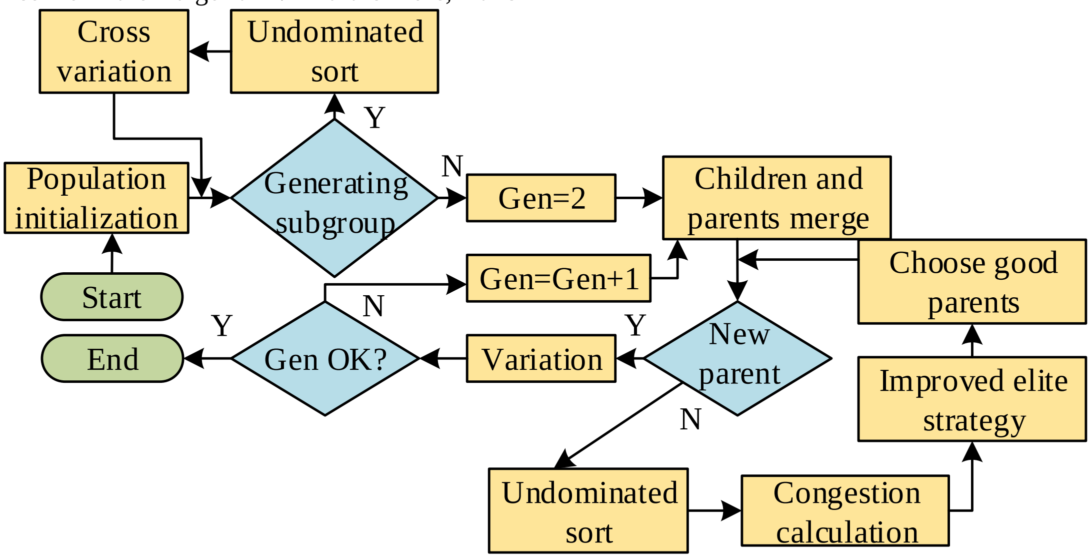

Fig. 6. Flowchart of NSGA-II.

IV. Performance Testing of NSGA-II in DTMS

To test the usability of the DTMS NSGA-II optimization algorithm (IM-NSGA-II) proposed by the research institute, this study chose to construct a virtual flexible job shop and conduct simulation experiments on its optimization ability. The software and hardware environment and parameter settings used in the study are shown in Table I. Through this configuration, the performance of the algorithm can be accurately and reliably evaluated, while also meeting the needs of daily development and testing. This study further introduces the same type of multi-objective optimization algorithm and compares it with the improved NSGA-II. It introduces the Multi Objective Evolutionary Algorithm on the ground of Decomposition (MOEA/D) and the Strength Pareto Evolutionary Algorithm 2 (SPEA2), respectively. The parameters of IM-NSGA-II are set as follows: Set the Population Size to 100, Crossover Probability to 0.9, Crossover Distribution Index to 20 and Mutation Distribution Index to 20. Selection is set to Binary tournament selection, Crossover is set to Simulated Binary Crossover and Polynomial Mutation. The parameters for MOEA/D are set as follows: The population Size is set to 100, the Neighborhood Size to 20%, the Weight Vector Update Interval to 50 generations, and the Crossover Probability to 1.0. The Crossover Distribution Index is set to 20, the Mutation Distribution Index to 20, and the Neighborhood Selection Probability to 0.9. The Replacement Strategy is set to adjacence-based replacement and the Decomposition Approach is set to Tchebycheff. SPEA2 parameters are set as follows: Population Size is 100, Archive Size is 100, Crossover Probability is 0.8, and Crossover Distribution Index is 20. The Mutation Distribution Index is set to 20, Selection is set to Binary tournament selection, Crossover is set to Simulated Binary Crossover, and Mutation is set to uniform variation. The maximum algebra for all algorithms is set to 120 generations.

TABLE I. Study Software and Hardware Environment

Local hardware environment			Software environment and parameter setting		
Local hardware	Detail	Argument	Name	Detail	Argument
Local hardware	Dell	Dell Precision 7760	Development language	Python	3.9.5
CPU	Intel® Core™ i9-11950H	2.60GHz, 8core	Database	Python DEAP	1.3.1
RAM	Kingston	8Gb*2,3200Mhz	Processing	NumPy	1.21.0
Harddisk	TOSHIBA	2TB	Visual tool	Matplotlib & Seaborn	Matplotlib 3.4.2 & Seaborn 0.11.1

Cloud server hardware environment			Development environment	Visual Studio Code	1.59.0
Cloud server provider	Alibaba Cloud	-	Container technology	Docker	20.10.7
Instance type	ecs.g6.4xlarge	-	Container orchestration	Kubernetes	1.21.2
CPU	Intel Xeon Gold	6149, 3.10Ghz, 16core	Q_{max}	-	200
RAM	Kingston	32Gb*4,3200Mhz	maxGen	-	100
Memory	Ultra Disk	2TB, SSD	Pc	-	0.9
System	Alibaba Cloud Linux	2.1903 LTS	Pm	-	0.1

TABLE II. COMPARISON OF STANDARD DEVIATION AND MEAN VALUE OF CONVERGENCE PERFORMANCE OF THREE ALGORITHMS

Times	IM-NSGA-II		MOEA/D		SPEA2	
	Mean	Standard	Mean	Standard	Mean	Standard
1	$5.417*10^{-6}$	$5.824*10^{-6}$	$4.628*10^{-5}$	$5.471*10^{-4}$	$4.218*10^{-3}$	$8.201*10^{-3}$
2	$6.279*10^{-6}$	$6.583*10^{-6}$	$5.210*10^{-4}$	$6.251*10^{-5}$	$6.394*10^{-3}$	$6.298*10^{-5}$
3	$7.251*10^{-6}$	$4.251*10^{-6}$	$5.069*10^{-5}$	$9.236*10^{-5}$	$8.275*10^{-3}$	$4.267*10^{-3}$
4	$4.987*10^{-6}$	$5.294*10^{-6}$	$6.364*10^{-4}$	$8.215*10^{-5}$	$5.364*10^{-4}$	$5.364*10^{-4}$
5	$5.687*10^{-6}$	$7.357*10^{-6}$	$7.207*10^{-5}$	$6.028*10^{-5}$	$5.227*10^{-3}$	$3.105*10^{-3}$
Average	$5.924*10^{-6}$	$5.862*10^{-6}$	$2.652*10^{-4}$	$1.689*10^{-4}$	$4.931*10^{-3}$	$4.676*10^{-3}$

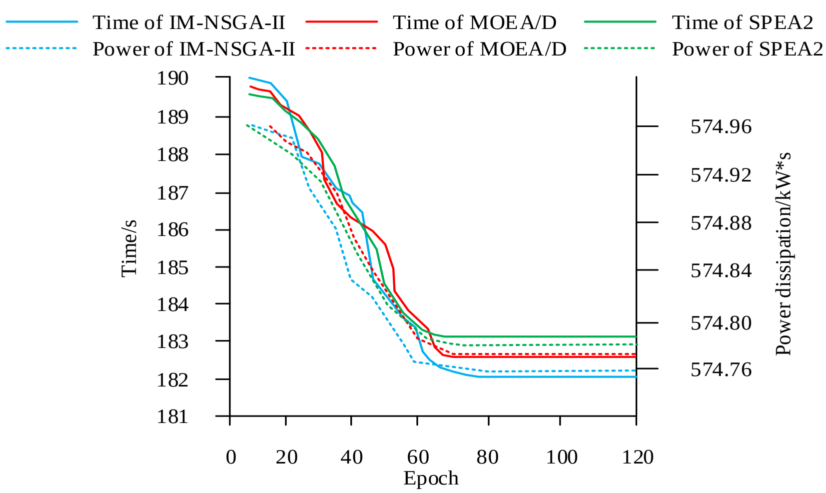

Fig. 7. The time and energy consumption of the three algorithms depend on the optimization performance of the iteration.

Firstly, the convergence performance of the three algorithms was tested, and the mean and standard deviation of the convergence performance of the three algorithms were tested. The test results are shown in Table II. Table II shows that the improved NSGA-II proposed by the research institute has better convergence performance in terms of mean and standard deviation. This proves that it has better convergence performance compared to MOEA/D and SPEA2, and can complete algorithm training at lower costs.

It tests the iterative performance of three algorithms and their impact on production time and energy consumption. The test results are shown in Fig. 7. Fig. 7 shows that the improved NSGA-II proposed by the research institute has the best optimization effect. It can reach its optimal state after about 60 iterations, and the optimized average production time is 181.9 seconds, saving 0.4 seconds and 1.1 seconds compared to MOEA/D and SPEA2, respectively. The optimal energy consumption performance after optimization is 574.75kW*s, which shows lower energy consumption compared to MOEA/D and SPEA2.

It compares and analyzes the Hypervolume (HV) indicators of three algorithms, and the analysis results are shown in Fig. 8. It shows that its HV indicator performs well, outperforming MOEA/D and SPEA2. The improved NSGA-II proposed by the research institute has better performance in multi-objective optimization problems, with better diversity and convergence compared to MOEA/D and SPEA2 algorithms.

The other conditions are kept the same, and the time optimization performance and energy consumption optimization performance of the three algorithms under multiple devices are tested. The test results are shown in Fig. 9. Fig. 9 shows that the optimization effect of the NSGA-II proposed by the research institute remains optimal under different device numbers. Compared to MOEA/D and SPEA2, its production time optimization effect for different quantities of equipment is 11.12% -21.37% higher, respectively. Compared to MOEA/D and SPEA2, its power optimization effect is 2.14% -6.89% ahead, respectively.

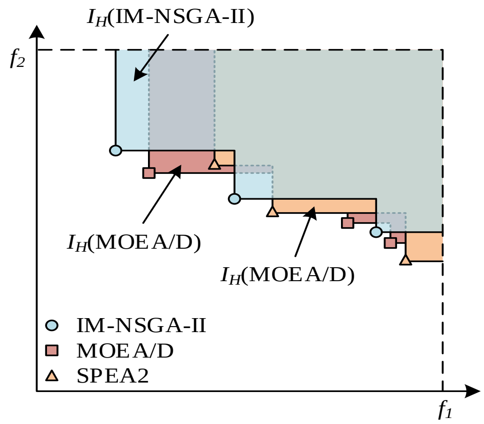

Fig. 8. HV index comparison results of three algorithms.

It sets up the same workpiece with a total of five process flows, and the number of optimization equipment faced by the three algorithms is fixed. The optimization effects of the three algorithms are compared, and the experimental results are shown in Table III. It shows that the optimization time of the improved NSGA-II proposed by the research institute reached 713.5 seconds. The optimization time of MOEA/D algorithm is 887.3s, and the optimization time of SPEA2 is 893.3s. Compared to MOEA/D and SPEA2, the production time of the improved algorithm has been reduced by 173.8s and 179.8s, respectively. The total power consumption of the improved optimization model is 2883.7kW*s, which is reduced by 32.0kW*s and 45.5kW*s compared to MOEA/D and SPEA2, respectively. The improved NSGA-II algorithm proposed by the research institute can reduce the time spent on production by the manufacturing system, reduce the total power consumption of the system, improve the performance of the manufacturing system, enable better simulation of the workshop, and achieve dynamic scheduling and energy efficiency optimization of the workshop. Due to the fact that the optimization time at this time did not consider the parallel processing of tasks, but simply summarized the processing time of different tasks, the result value was too high. In the process of scheduling optimization, different optional equipment groups are allocated based on the overall processing time, thereby reducing equipment processing time and optimizing workshop processing energy consumption. In order to better reflect the importance of the improved NSGA-II algorithm, a Gantt chart was drawn to reflect its final optimization results. The Gantt chart is shown in Fig. 10.

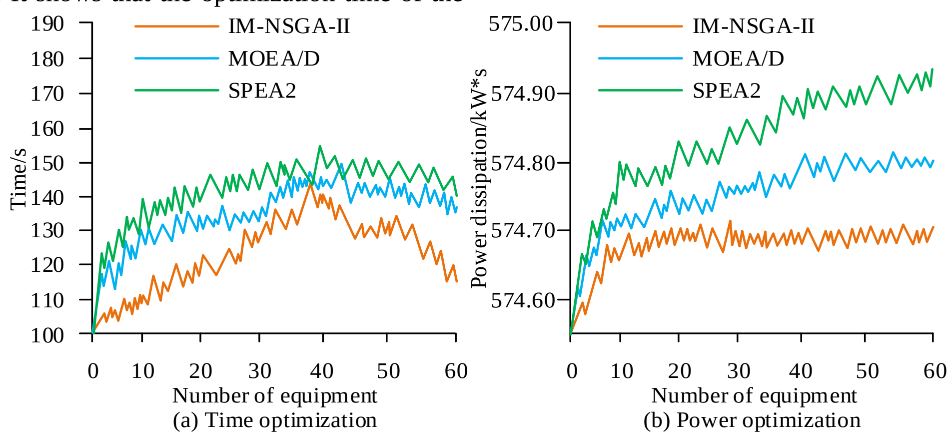

Fig. 9. Optimization performance comparison of three algorithms under different number of devices.

TABLE III. COMPARISON OF ACTUAL INDUSTRIAL OPTIMIZATION PERFORMANCE OF THREE ALGORITHMS

Process flow	NSGA-II		MOEA/D		SPEA2	
	Time/s	Power /kW*s	Time/s	Power /kW*s	Time/s	Power /kW*s
1	133.7	576.2	167.9	581.9	172.5	586.4
2	144.8	577.1	179.8	584.6	181.3	585.2
3	147.2	576.8	183.4	582.4	185.2	586.3
4	166.2	577.3	189.7	583.9	176.9	587.1
5	121.6	576.3	166.5	582.9	177.4	584.2
Total	713.5	2883.7	887.3	2915.7	893.3	2929.2

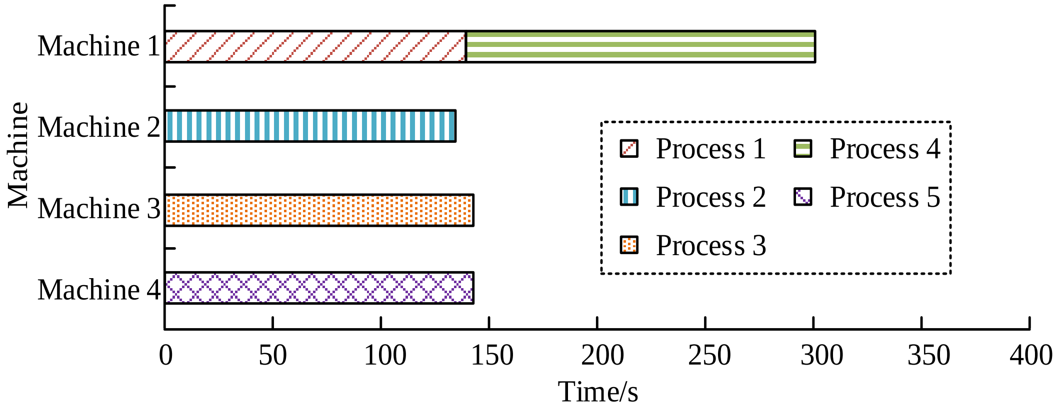

Fig. 10. Gantt chart of process flow.

From Fig. 10, it can be seen that after merging the process flow, the final optimization time of the improved NSGA-II algorithm is 299.9s. Compared to the previous simple time addition, the value decreased by 413.6 seconds. It can be seen that the improved NSGA-II algorithm can enhance the performance of the digital twin manufacturing system, and can achieve dynamic scheduling and energy efficiency optimization in the real workshop more quickly in the system.

V. Conclusion

With the development of Industry 4.0, the intelligence and real-time of industry have become a trend. However, further optimization of industry and manufacturing has become a challenging issue, and DTMSs have proposed solutions for this. On the ground of the improved NSGA-II, targeted improvements were made to its elite retention strategy to improve its diversity. On the ground of this algorithm, a multi-objective optimization approach was adopted to optimize production time and energy consumption. The experiment showcased that the optimization method on the ground of NSGA-II has better convergence performance compared to MOEA/D and SPEA2. The optimized average production time was 181.9 seconds, which saved 0.4 seconds and 1.1 seconds compared to MOEA/D and SPEA2, respectively. The optimal energy consumption performance after optimization was 574.75kW*s, which showed lower energy consumption compared to MOEA/D and SPEA2. Its HV indicators performed well with better diversity. Compared to MOEA/D and SPEA2, the production time optimization effect for different numbers of devices was 11.12%-21.37% higher, and the power consumption optimization effect was 2.14%-6.89% higher. This study provided a new method for optimizing DTMSs by improving the elite retention strategy of the NSGA-II, which can provide more effective methods for system optimization in the manufacturing industry. However, this method did not take into account force majeure factors such as equipment failures and fluctuations in raw material prices in actual production and manufacturing. In future research, in-depth research should be conducted on this issue to improve the applicability and practicality of the optimization method.

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References

[1] Kirmizi M, Kocaoglu B. 2022. Digital transformation maturity model development framework based on design science: case studies in manufacturing industry. Journal of Manufacturing Technology Management, 33(7): 1319-1346.

[2] Shen Z, Xu W, Li W, Shi Y, Gao F. 2023. Digital twin application for attach detection and mitigation of PV-based smart systems using fast and accurate hybrid machine learning algorithm. Solar Energy, 250(1): 377-387.

[3] Fisher C R, Nygren K E, Beaudoin A J. 2022. Validation of materials-informed digital twin: Mapping residual strains in HSLA steel weldment using high energy X-rays. Journal of manufacturing processes, 74(2): 75-87.

[4] Khan A, Shahid F, Maple C, Ahmad A, Jeon G. 2022. Toward Smart Manufacturing Using Spiral Digital Twin Framework and Twinchain. IEEE transactions on industrial informatics, 18(2): 1359-1366.

[5] Fukawa N, Rindfleisch A. 2023. Enhancing innovation via the digital twin. Journal of product innovation management, 40(4): 391-406.

[6] Liu S, Lu Y, Shen X, Bao J. 2023. A digital thread-driven distributed collaboration mechanism between digital twin manufacturing units. Journal of Manufacturing Systems, 68(1): 145-159.

[7] Guo D, Zhong R Y, Rong Y, Huang G G Q. 2023. Synchronization of Shop-Floor Logistics and Manufacturing Under IIoT and Digital Twin-Enabled Graduation Intelligent Manufacturing System. IEEE transactions on cybernetics, 53(3): 2005-2016.

[8] Fan Y, Yang J, Chen J, Hu P, Wang X, Xu J, Zhou B. 2021. A digital-twin visualized architecture for Flexible Manufacturing System. Journal of Manufacturing Systems, 60(1): 176-201.

[9] Chetan M, Yao S, Griffith D T. 2021. Multi-fidelity digital twin structural model for a subscale downwind wind turbine rotor blade. Wind Energy, 24(12): 1368-1387.

[10] Osho J, Hyre A, Pantelidakis M, Ledford A, Harris G, Liu J, Mykoniatis K. 2022. Four Rs Framework for the development of a digital twin: The implementation of Representation with a FDM manufacturing machine. Journal of Manufacturing Systems, 63(1): 370-380.

[11] Singh G, Banga V K. 2022. Combinations of novel hybrid optimization algorithms-based trajectory planning analysis for an industrial robotic manipulators. Journal of Field Robotics, 39(5): 650-674.

[12] Wu D, Wu L, Ye Y. 2022. Industrial structure optimization, economic development factors and regional economic risk prevention in post COVID-19 period: empirical analysis based on panel data of Guangdong regional economy. Journal of combinatorial optimization, 44(5): 3735-3777.

[13] Sekaran R, Munnangi A K, Rajeyyagari S, Ramachandran M, Aiturjman F. 2021. Ant colony resource optimization for Industrial IoT and CPS. International Journal of Intelligent Systems, 37(12): 10513-10532.

[14] Chen Y, He S, Jin X, Wang Z, Wang F, Chen L. 2023. Resource utilization and cost optimization oriented container placement for edge computing in industrial internet. Journal of supercomputing, 79(4): 3821-3849.

[15] Morse L, Mallardo V, Aliabadi F M H. 2022. Manufacturing cost and reliability-based shape optimization of plate structures. International Journal for Numerical Methods in Engineering, 123(10): 2189-2213.

[16] Liu H, Jin X. 2020. Digital manufacturing course framework for senior aircraft manufacturing engineering undergraduates. Computer Applications in Engineering Education, 28(2): 338-356.

[17] Gazman V D A. 2023. New Criterion for the ESG Model. Green and Low-Carbon Economy, 1(1), 22–27.

[18] Negri E, Berardi S, Fumagalli L, et al. 2020. MES-integrated digital twin frameworks - ScienceDirect. Journal of Manufacturing Systems, 56(58): 58-71.

[19] Choudhuri S, Adeniye S, Sen A. 2023. Distribution Alignment Using Complement Entropy Objective and Adaptive Consensus-Based Label Refinement for Partial Domain Adaptation. Artificial Intelligence and Applications. 1(1): 43-51.

[20] Liang Z, Wang S, Peng Y, Mao X, Yuan X, Yang A. 2022. The process correlation interaction construction of Digital Twin for dynamic characteristics of machine tool structures with multi-dimensional variables. Journal of Manufacturing Systems, 63(1): 78-94.