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Intelligent Assembly Scheduling of Large Laser Devices Based on Neural Network

Zhao XIONG[1], Chengcheng WANG and Dongxia HU
Laser Fusion Research Center, CAEP, Mianyang 621900, China

Abstract. Aiming at the dynamic flexible scheduling problem in the integrated installation of large-scale laser devices, a deep learning rule acquisition method based on artificial neural network is proposed. Firstly, the typical example is optimized by genetic algorithm, then the task comparison trajectory and characteristic data are extracted from the optimal solution, and the task priority model is generated by deep learning. Finally, the dynamic flexible scheduling decision mode is constructed based on the algorithm model, so as to realize fast response and accurate scheduling in complex, changeable and uncertain production environment. Data experiments and practical cases verify the effectiveness of this method. With the increase of the number of scheduling objects, the computational efficiency of ANN scheduling algorithm is obviously better than GA algorithm in the case of little difference in calculation results.

Keywords. Large laser devices, artificial neural network, deep learning rule, flexible scheduling

1. Introduction

Large-scale laser device is an important infrastructure for studying fusion clean energy, and it is a typical scientific apparatus. Because of its large scale, high precision and high cleanliness, the integrated installation of the device is facing great challenges [1]. In order to complete the task of precision assembly and calibration of tens of thousands of optical-mechanical modules in this device and improve the efficiency and quality consistency of assembly and calibration, a digital workshop for intelligent manufacturing has been built, and the research on intelligent scheduling in precision assembly and calibration management and control platform is an important topic. This kind of problem belongs to flexible assembly job shop scheduling problem, and heuristic scheduling rules are commonly used to solve it in practical applications. Especially, It is necessary to respond quickly to emergencies in the process of precision assembly and calibration, and seek the optimal solution through intelligent scheduling to ensure that the expected scheduling goals are achieved. In a word, although rule scheduling has been widely used, its local optimization characteristics lead to poor solution quality, and no scheduling rule can achieve better solution performance than other scheduling rules in any scheduling scenario and performance index [2]. Zhang Zequn et al [3] adopted rule-based fully reactive scheduling to realize self-organized production in discrete workshops.

[1] Corresponding author: xiong_022111@163.com

In recent years, with the vigorous development of machine learning technology, many scholars have applied it to the field of production scheduling. Mouelhi-Chibani W et al[4] proposed a neural network model to select appropriate scheduling rules for the dynamic shop scheduling problem. Golmohammadi [5] proposed a decision support model based on neural network, which can predict the scheduling target value without real scheduling. Zhang Liping et al [6] proposed a job shop scheduling rule discovery method, which extracts high-quality training samples from near-optimal scheduling schemes. Experiments show that it can significantly improve the rule scheduling performance.

2. Problem description and modeling

2.1. Brief introduction of precision assembly and calibration process

Precision assembly and calibration process mainly includes optical element cleaning, optical element coating, mechanical frame cleaning, mechanical frame baking, optical-mechanical integrated assembly and other links, in which optical element and mechanical frame cleaning can be processed in parallel, and optical-mechanical assembly can be carried out after they are completed. Optical-mechanical assembly is a core process link, including mechanical parts assembly and optical assembly. The typical product process is shown in Figure 1.

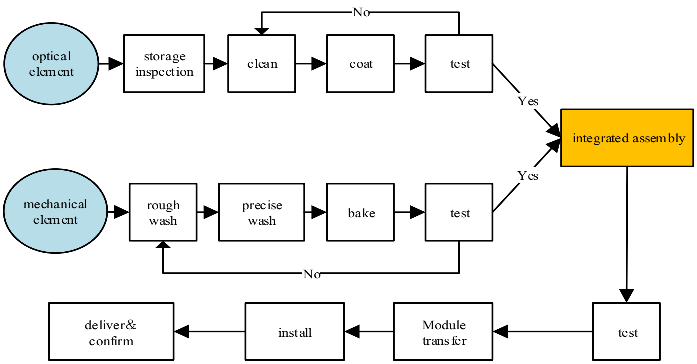

Figure 1. Typical optical-mechanical modules precision assembly and calibration process[7].

2.2. Problem hypothesis

The scheduling problem between precision assembly workshop should also include the following assumptions:

1) All optical and mechanical modules and equipment are in ready state at 0:00.

2) A piece of equipment can only be installed and calibrated in one process at the same time.

3) The same process can only be installed and calibrated in one equipment at the same time.

4) No interruption is allowed once the process begins.

5) Only considering the sequence constraint of process processing in the same optical-mechanical module, the process priority among different optical-mechanical modules is the same.

6) Do not consider the problem of multiple rework caused by detection, and ensure that there is only one follow-up node in each process.

3. Solution method

3.1. Overall framework

Aiming at the job shop scheduling problem of integrated installation in large-scale laser devices, Proposed a deep learning rule generation method based on Artificial Neural Network (ANN). The overall framework of this method is shown in Figure 2.

In the off-line learning stage, firstly, according to the device structure and process data, each bundle group plan of the device is decomposed, and multiple assembly calibration tasks are generated as typical test examples of precision assembly school bus rooms; Then, the approximate optimization solution of the example is obtained by multiple iterations of genetic algorithm; Then, the task comparison trajectory is obtained from the optimal solution as the machine learning training and verification data set; Finally, artificial neural network method is used to supervise and learn, and a scheduling rule model based on ANN is formed.

In the online application stage, the scheduling algorithm based on ANN scheduling rules is adopted. ANN scheduling model can return the priority relationship of tasks only by passing in the relevant features of tasks to be compared, so as to quickly complete the dynamic scheduling of flexible assembly job shop. After the scheduling is completed, the control instructions will be automatically issued and executed through the control platform of the precision loading school bus room, and the instruction execution status can be automatically obtained from the Internet of Things. Due to the dynamic uncertainty between precision loading buses, the system supports two rescheduling modes: periodic trigger and critical abnormal event trigger. Online application constructs a constantly updated closed-loop decision-making mode of "production state awareness-scheduling analysis and decision-scheduling precise execution".

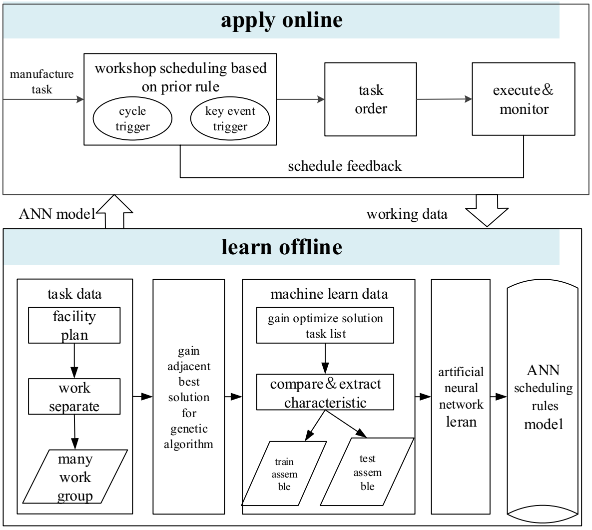

Figure 2. A Framework for solving flexible scheduling problem based on deep Learning

3.2. Genetic algorithm to obtain optimal solution

After the task data is generated, genetic algorithm is selected to solve the approximate optimal scheduling scheme. Generally speaking, genetic algorithm imitates the mechanism of biological heredity and natural selection, and simulates the evolution process of organisms by computer, so as to realize global optimization search [8].

Genetic algorithm uses permutation method to encode genes, and uses natural numbers between 1 and n to express the priority order among working procedures, where n is the total number of all working procedures. When decoding, the assignment order of the working procedure tasks is read out from the chromosome code, and the tasks are assigned one by one according to the order, so as to obtain the fitness of the chromosome code. In genetic operation, binary tournament is used for selection, partial mapping crossover operator is used for crossover operation, and exchange node method is used for mutation operation; Termination conditions have been evaluated more than 50,000 times.

3.3. Feature modeling

Combined with the problem description and model, six features shown in Table 1 are selected as comparison items among processes, and the specific calculation methods of these six features are consistent with those in reference [9].

Table 1. Input characteristics of deep learning network.

No.	characteristics	remark
1	PTC	processing time of current operation
2	ESP	earliest start time of current operation
3	WIQC	machining queue length of work center in current operation
4	WINQ	machining queue length of work center in next operation
5	NOPT	processing time of next operation
6	SRPT	Remaining processing time of scheduling objec

As shown in Fig. 3, the process priority model based on artificial neural network, ANN acts as a binary classifier, and the output value Y is 0 or 1.

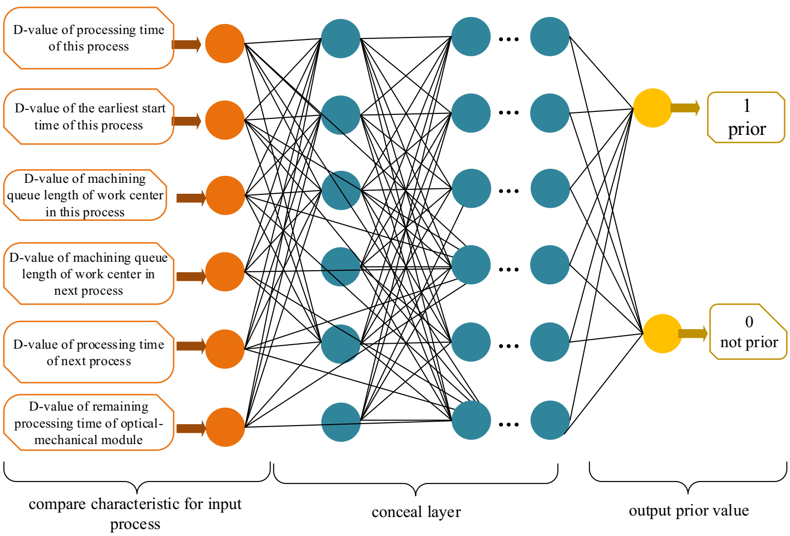

Figure 3. Task priority model based on deep learning network

3.4. Task comparison trajectory data acquisition

According to the optimized solution sequence obtained by genetic algorithm, the task comparison trajectory data is obtained as the training and testing data of machine learning. The specific practice is shown in Figure 4: Optimize and solve the task queue in turn, such as Task 1 in the figure, obtain all the tasks with 0 entry in the process network constraint when Task 1 is assigned, and then generate (1, 8), (1, 5) and (1, 4) three groups of task comparison tracks for these tasks, with the eigenvalue label of 1; At the same time, three groups of reverse comparison tracks (8, 1), (5, 1) and (4, 1) are generated, and their characteristic labels are 0.

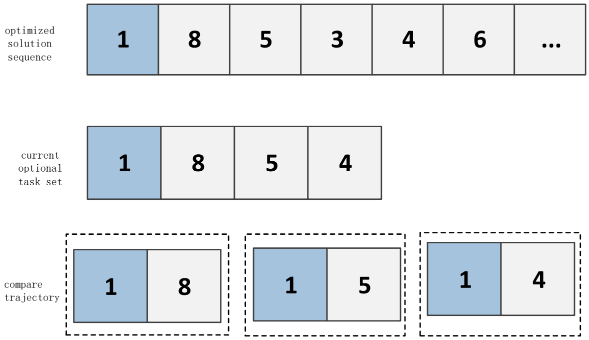

Figure 4. Task comparison trajectory based on genetic algorithm case

After obtaining the process comparison trajectory, it is necessary to obtain six comparative feature data according to the requirements of feature modeling.These characteristic data are normalized, so as to eliminate the adverse effects caused by singular sample data.

3.5. Artificial neural network learning

After the task comparison trajectory data is ready, the open source machine learning framework Encog is used to obtain the binary classification model. Encog supports a variety of learning algorithms and provides a wealth of neural network algorithm functions, including a variety of normalization and data processing support classes. The neural network adopts full connection mode, the input layer is the comparison vector between tasks, and five hidden layers are set in the middle. Because the output needs to be compressed into the interval of [0, 1], the Sigmoid activation function is adopted.

$$\mathrm{f}(x) = \frac{1}{1+\mathrm{e}^{-\mathrm{x}}} \tag{1}$$

The loss function adopts binary cross entropy function. This function can effectively punish the prediction results of the model for misclassified samples, thus improving the performance of the model. Bivariate cross entropy function is a common loss function, which is suitable for binary classification problem. The calculation formula is as follows:

$$\mathrm{Loss} = -\frac{1}{\mathrm{n}}\sum_{i=1}^{\mathrm{n}}\left[y_i \cdot \log p(y_i) + (1-y_i)\cdot \log(1-p(y_i))\right] \tag{2}$$

Where $\mathrm{y_i}$ is the binary tag value 0 or 1, and $\mathrm{P(\,y_i)}$is the probability of belonging to the tag value of $\mathrm{y_i}$.

3.6. Scheduling based on priority rules

On-line scheduling adopts the scheduling method based on priority rules. According to the priority rules, the process tasks to be arranged are assigned to the equipment one by one to form a detailed process operation plan. The algorithm flow is shown in Figure 5:

1) According to the working procedure task network, the working procedure task set with 0 (all the pre-working procedures have been scheduled) is obtained, and the arrangable task set is constructed.

2) According to the Job Select Rule (SR), the task can be arranged to sort, and the highest priority is selected. This algorithm supports many types of JSR scheduling finite rules. If the priority of the two tasks is the same, random selection is made.

3) Choose the equipment with the highest priority to arrange, and adopt the earliest start rule, that is, select the equipment that can be assembled at the earliest.

4) Subsequent working procedure tasks, and then updating the set of arrangable working procedure tasks, and circulating in turn until all tasks are arranged.

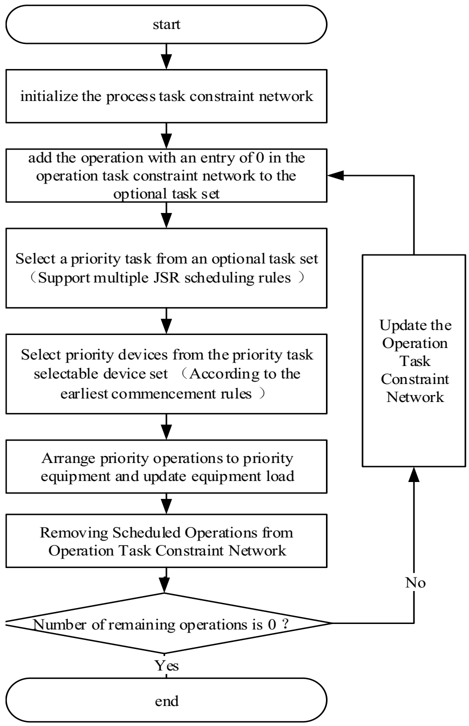

Figure 5. Flexible scheduling process based on integrated installation scheduling rules

4. Numerical experiment

The main equipment of precision assembly and calibration automatic assembly workshop includes 2 lifting and coating machines, 6 cleaning equipment, 3 high-temperature baking equipment, 2 automatic assembly stations for mechanical parts, 4 automatic assembly stations for optical machines, etc. Typical optical-mechanical module process and working hours are shown in Table 2.

Table 2. Process flow and corresponding working hours of typical optical modules.

Serial number	Operation name	processing time /(h)
1	optical elements inspecting	2
2	optical elements cleaning	9
3	coating of optical element	2.7
4	Detecting of optical element detection	2
5	warehousing inspection of mechanical frame	0.2
6	mechanical frame rough washing	0.25
7	mechanical frame fine washing	0.5
8	mechanical frame high temperature baking	1.12
9	cleanliness detecting of mechanical frame	2
1	assembling of mechanical	12
11	assembling and testing of optical-mechanical	6
12	storage and Transfer	4.8

Eight examples are listed in Table 3, where Column N represents the number of optical-mechanical modules, Column C represents the scheduling target value, and Column T (s) represents the running time.Compared with the traditional heuristic rule algorithms FIFO, SPT and LWKR, only the first example has a slightly poor scheduling effect, and the other seven examples have significant advantages. Moreover, through data comparison and analysis, it is also found that with the increase of the number of optical-mechanical modules, the advantages of ANN scheduling algorithm are more obvious. Compared with GA, ANN rule algorithm has some gaps in performance, but the gap range is within 6%. However, genetic algorithm has a huge amount of computation, and the scheduling time of 15 optical-mechanical modules is more than 10 min, which can not adapt to the highly dynamic and uncertain environment of precision assembly and calibration process.

Table 3. Scheduling results of five intelligent algorithms.

No.	n	FIFO		SPT		LWKR		ANN		GA	
		C	T(s)	C	T(s)	C	T(s)	C	T(s)	C	T(s)
1	5	39.2	0.18	36.9	0.19	34.1	0.22	33.9	0.64	33.3	281
2	5	40.9	0.29	36.4	0.21	37.8	0.24	35.8	0.69	34.1	296
3	10	52.0	0.38	58.0	0.42	51.0	0.47	43.7	0.89	43.1	512
4	10	63	0.40	56.2	0.43	63.1	0.53	50.3	0.88	48.3	556
5	15	65.7	0.60	66.6	0.63	74.8	0.78	60.4	1.22	57.12	615
6	15	67.1	0.62	66.3	0.64	62.2	0.82	55.4	1.18	52.8	678
7	20	121.3	0.90	121.7	0.93	116.1	1.08	103.6	1.54	100.0	1010
8	20	120.7	0.96	116.9	0.96	115.0	1.18	103.7	1.49	101.4	998

5. Practical application

Figure 6 shows the scheduling result resource Gantt chart of ANN algorithm. The intelligent dispatching system based on ANN rule has been integrated in the control platform of precision assembly and calibration of a large laser device in CAEP. The system can automatically schedule according to the real-time status of the site, and issue the dispatching control instructions to the corresponding production equipment through the Internet of Things platform, thus realizing the automatic series operation between the loading buses with intelligent scheduling as the core.

In the simulation process of the system, the intelligent scheduling system can achieve second response to abnormal emergencies, and the deviation of scheduling results is controlled within 10%. The system effectively solves the problems of unsatisfactory solution quality and unsustainable optimization of traditional heuristic methods, and becomes an important means of efficient operation in precision assembly and calibration workshop.

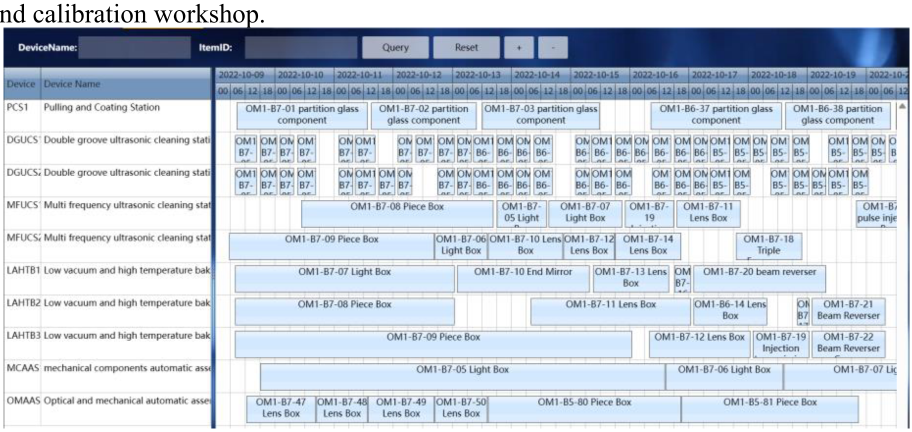

Figure 6. Result diagram of intelligent scheduling system in automatic assembly shop.

6. Concluding remarks

Aiming at the dynamic problem of intelligent assembly scheduling in large-scale laser equipment, an integer programming model of flexible assembly shop considering the serial-parallel relationship of optical-mechanical module processes is established, and a scheduling rule acquisition method based on artificial neural network is proposed. This method extracts the task comparison trajectory from the optimization solution of genetic algorithm as training data, and uses artificial neural network to learn the scheduling task priority model. Data experiments show that the scheduling results of this method are significantly better than the traditional heuristic scheduling rules, and good results have been achieved in practical application.

In the future, we will further study the effectiveness of more job-shop scenario verification algorithms, consider the influence of clean cache capacity, detection rework and other factors in the assembly and calibration process, and start to study an adaptive scheduling method for assembly and calibration process based on multi-intelligent agents.

References

[1] Zheng Wanguo, Deng Ying, ZhouWei, et al. Development of lasertechnology in Research Center of Laser Fusion[J]. High Power Laser and Particle Beams, 2013, 25(012):3082-3090.
[2] Burke E K , Hyde M , Kendall G , et al. A survey of hyper-heuristics. Office for Official Publications of the European Communities, 2009.
[3] Zhang Zequn, Tang Dunbing, Jin Yongqiao, et al.Self-organizing Production Scheduling Technology of Discrete Shop Driven by Information IoT [J]. Journal of Mechanical Engineering, 2018, 54: 34-44.
[4] Mouelhi-Chibani W, Pierreval H. Training a neural network to select dispatching rules in real time[J]. Computers & Industrial Engineering, 2010, 58(2):249-256.
[5] Golmohammadi D. J. I. J. o. P. R. A neural network decision-making model for job-shop scheduling[J]. 2013, 51: 5142-5157.
[6] Zhang L, Hu Y,Wang C , et al. Effective dispatching rules mining based on near-optimal schedules in intelligent job shop environment[J]. Journal of Manufacturing Systems, 2022(63-):63.
[7] Xiong Zhao, Yin Lingyu, Pei Guoqing, et al. Intelligent assembly scheduling for large laser devices[J]. High Power Laser and Particle Beams, 2023,35(9):092002.
[8] Holland J.H. Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence [M]. Cambridge, MA: MIT Press, 1992. (9).
[9] Panwalkar S. S, Iskander W. J. O. R. A Survey of Scheduling Rules[J]. 1977, 25: 45-61.(10).