Optimization design of assembly scheme based on network analysis heuristic algorithm

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Abstract. Aiming at the problem of efficiency and cost optimization in the production of intelligent robots, traditional methods are difficult to solve complex problems such as multi-layer capacity limitation, assembly delay and equipment maintenance collaborative optimization, and the research is simplified.The innovation of this study lies in constructing a three-layer capacity-constrained batch production model, breaking through the single-level optimization limitations of previous research. This model realizes cross-layer coordination among production scheduling, assembly delay handling, and equipment maintenance. Meanwhile, a multi-algorithm synergy system is established: a dynamic programming heuristic algorithm is used to solve the model, reducing costs; a genetic algorithm is integrated to cope with assembly delays; a simulated annealing method optimizes the maintenance plan; and time series analysis accurately predicts requirements. This integration of a systematic model and multiple algorithms provides a holistic solution to complex production constraints. The results show that the model reduces inventory and delay costs and ensures production continuity. The performance is better than the traditional method and reduces the loss of prediction error. This study provides a systematic optimization strategy for intelligent robots and similar production systems to help production automation and intelligence.

Keywords: Production Optimization, Network Analysis, Genetic Algorithm, Simulated Annealing Method, Time-Series Forecasting.

1. Introduction

With the rapid development of intelligent technology, the water pipeline cleaning robot faces the complex production management problem of multi-component collaborative assembly due to the increase of market demand. The traditional production scheduling method is inefficient in dealing with multi-level capability constraints, component assembly time delay and equipment maintenance collaborative optimization, and needs systematic solutions. In the existing research, Li Chang[1]established a two-layer dynamic batch mathematical model with limited capacity for assembly line production planning and parts inventory strategy in 2010, and optimized the system batch and total cost by heuristic algorithm to reduce short-term production cost. Chen Mingzhi 's team[2]constructed a grid warehouse model for intelligent warehouse logistics robot scheduling in 2019. Based on multi-layer coded genetic algorithm and Q-Learning algorithm, the agent path optimization was realized, and the operation performance was improved by more than 20%. In 2025, Hao Yue 's team[3]established a multi-objective stochastic programming model for the uncertainty of truck scheduling in open-pit mines, and improved the scheduling efficiency and balance through genetic annealing hybrid algorithm. However, these studies are limited to a single optimization level, and do not solve the dynamic coupling problem of multi-layer production capacity constraints, time delay effect and equipment maintenance cycle.In view of this, this paper focuses on the shortcomings of multi-level capacity constraints in the production of water pipeline cleaning robots, the conflict between component assembly time delay and inventory cost, and the lack of coordination between equipment maintenance and production continuity. A three-tier capacity-constrained batch model including assembly, sub-assembly and parts ordering is constructed. The network analysis heuristic algorithm, genetic algorithm and simulated annealing technology are integrated, and the autoregressive time series model is introduced to integrate demand forecasting to form an integrated solution that takes into account cost optimization, production continuity and demand response. The structure of this paper is as follows : The first chapter is the introduction, pointing out the shortcomings of the existing methods, and proposing the goal of constructing a three-layer capacity-constrained batch model ; the second chapter is the related theory, introduces the product structure, model architecture and core algorithm ; the third chapter is the experiment. Based on the actual data, three types of models are constructed, combined with the advantages of AR prediction and verification ; the fourth chapter is the conclusion, which describes the experimental ideas and processes in detail ; the fifth chapter is a summary of the research significance.

2. Related Theories

The assembly of underwater robot[4]shows that the data of this paper are from the actual production scene of an intelligent equipment manufacturing enterprise. The WPCR device produced by the factory is composed of 3 container boats, 4 robot arms and 5 power systems. Each component is composed of different sub-components. For example, the container boat is composed of controller, oar, perceptron and so on. The factory takes one week as the production planning period, only WPCR has external demand, and the production of container boat, machine arm and power system strictly occupies the working hours of key equipment with the standard of 3 hours / piece, 5 hours / piece and 5 hours / piece respectively.

The basic structure of the three-layer capacity-constrained model[5]: A three-layer capacity-constrained assembly system batch model is established for the deterministic finite-time assembly production planning and parts ordering problem as follows : Figure 1.

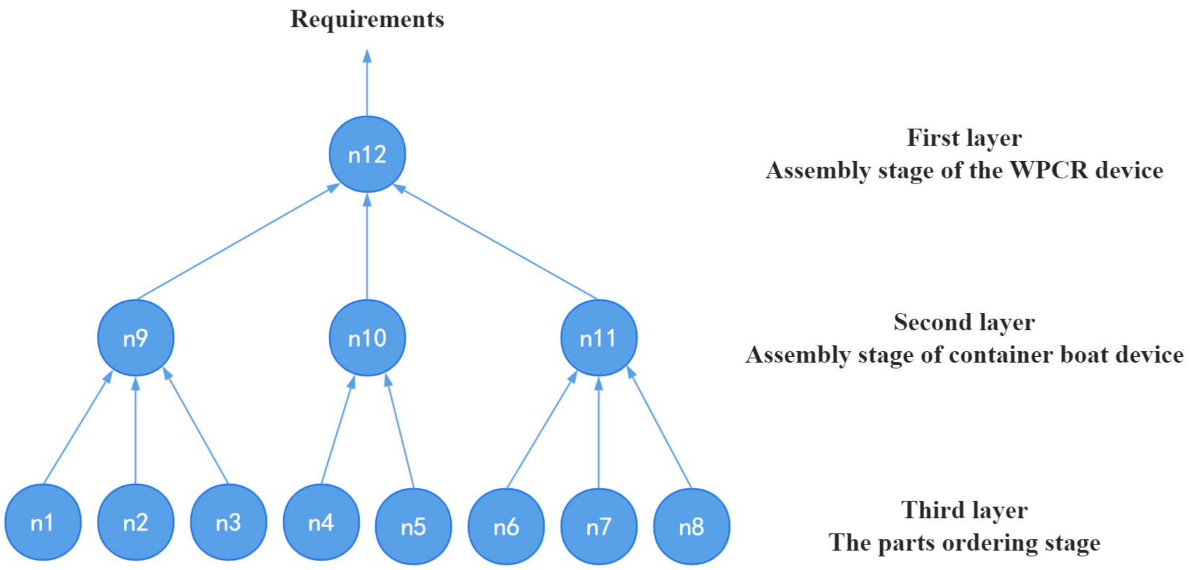

Figure 1. Schematic diagram of the assembly system

The first layer is the assembly stage of the WPCR device. According to the requirements of the order, the production plan is formulated and the container ship assembly is arranged without productivity restrictions. The second layer is the container ship assembly stage. According to the production plan of the first layer, the production plan of each container ship is formulated, the assembly output is arranged, and the productivity is limited. The third layer is the order stage of parts. According to the production plan of the second layer, the order strategy of each part is formulated, and the order quantity of parts is not limited.

3. Experments

The purpose of this experiment is to realize the scheduling optimization and cost control of intelligent robot water pipe cleaning production by constructing mathematical model and optimization algorithm. The overall process revolves around a three-tier core model : Model 1 constructs a capacity-constrained batch production model, and uses a dynamic programming heuristic algorithm to balance component availability and cost ; model 2 introduces time constraints, and optimizes the scheduling strategy of component delay assembly by genetic algorithm. Model 3 focuses on equipment maintenance, using 0-1 variables and simulated annealing method[6]to plan maintenance interval and production plan. In addition, the AR time series model is combined to predict the demand and integrated into the production model to verify the adaptability.

Through the above research and analysis, a series of optimization strategies and key conclusions on production scheduling, cost control and equipment maintenance are obtained, as shown below.

(1) Three-layer capacity-constrained production model

A three-layer capacity-constrained batch model, which includes three levels of assembly, sub-assembly and parts ordering. In the process of model establishment, in this paper need to take into account the time consumption of production equipment to ensure that the production efficiency is maximized without exceeding the capacity of the equipment. Since there is usually no polynomial-time exact solution algorithm for such problems, in this paper, will use a dynamic programming method based on network analysis[7]and a heuristic algorithm[8]to solve the problem in order to find a cost-minimizing production strategy.The idea of establishing the model is as follows : Figure 2.

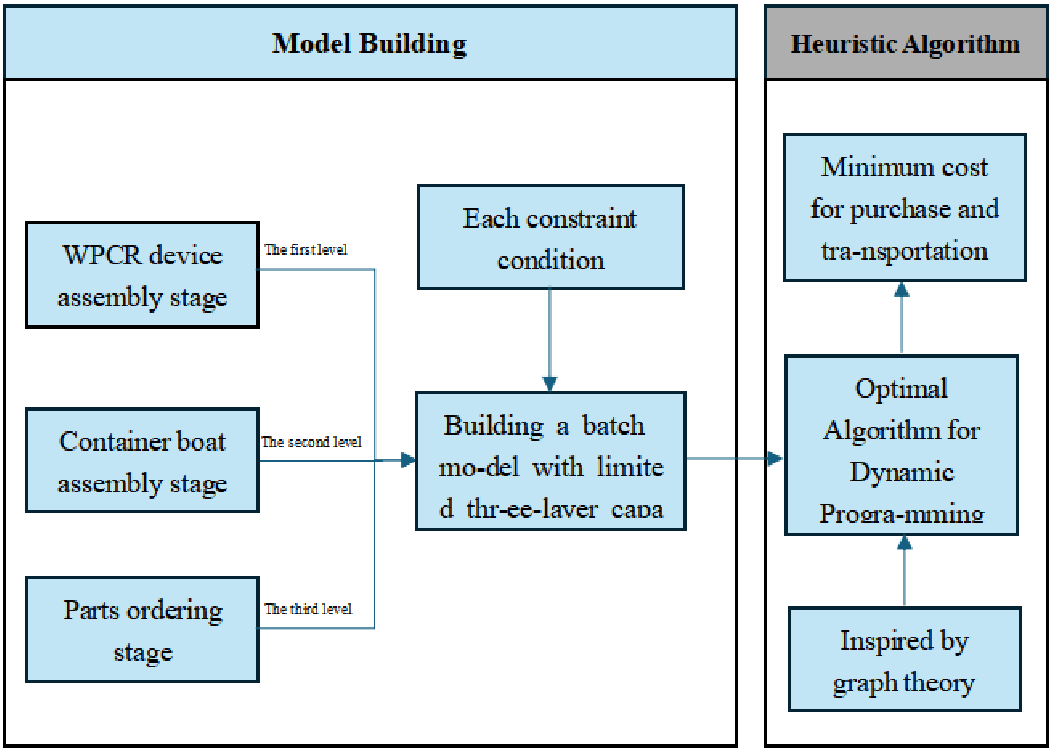

Figure 2. Flow chart of model building ideas

(2) Improved batch model of assembly system

Model introduction : On the basis of the three-layer capacity-constrained batch model, aiming at the complex time constraints of component preparation and assembly in actual production, a new constraint of " components must be assembled every other day " is introduced. By adjusting the model constraints, under the premise of using the original model structure and solution method, the influence of this change on the optimization results of production plan is analyzed in detail, so as to ensure the unity of theoretical efficiency and practical operation flexibility adaptability of production system.

The principle of genetic algorithm[9]: The genetic algorithm is derived from the theory of biological evolution, especially the theory of natural selection. It takes the fitness function as the evaluation standard, and optimizes the solution of the problem in the iterative search by simulating the biological genetic mechanism such as crossover and mutation. Different from exhaustive method and heuristic algorithm, it has the characteristics of adaptive search for global optimal solution, no need for continuous derivability of objective function, parallel processing of multiple potential solutions and direct operation of parameter coding form. In the genetic algorithm, the gene corresponds to the element of the solution of the problem space, the chromosome is composed of genes and represents a solution, the fitness is the value of the objective function space, the individual is uniquely identified by the chromosome and the fitness, and the group represents multiple solutions. The basic implementation steps are to define the solution space and coding method, construct the fitness function, set the population size and other parameters, and gradually obtain the optimal solution of the problem by simulating the biological evolution process.

(3) A production model to ensure the sustainability of production

Model Introduction : In actual production, equipment maintenance is the key to long-term stable operation of production, which can not only ensure equipment performance, but also improve production efficiency. For this reason, the constraint of ' 7 days of equipment maintenance within 30 weeks and maintenance interval of not less than 6 days ' is added, and the factors of equipment performance improvement after maintenance are considered. By introducing new decision variables and modifying the extended constraints, the dynamic programming heuristic algorithm based on network analysis is used to solve the production plan that meets the production demand and minimizes the cost, which helps to deeply understand the impact of maintenance activities on the production system and realize the economy and efficiency of the production plan[10].

4. Results

By constructing a three-layer capacity-constrained batch production model, combined with dynamic programming heuristic algorithm, genetic algorithm and simulated annealing method for experimental derivation, the following key results are obtained, as shown in Table 1 and Table 2.

Table 1. Solution results of models 1 and 2

Model	Date	WPCR assembly quantity	A assembly quantity	B assembly quantity	C assembly quantity	Production preparation costs	Inventory fees
Mass production model of a three-tier assembly system with limited capacity	Monday	39	177	156	195	1200	0
	Tuesday	36	108	144	180	1200	0
	Wednesday	40	120	160	200	1200	10
	Thursday	38	114	152	192	1200	0
	Friday	37	111	148	185	1200	0
	Saturday	46	138	184	230	1200	65
	Sunday	27	81	108	135	1200	0
	Sum	263	789	1052	1315	8475	
Model	Date	WPCR assembly quantity	A assembly quantity	B assembly quantity	C assembly quantity	Production preparation costs	Inventory fees
Genetic algorithms	Monday	39	108	144	180	1200	27828
	Tuesday	36	129	172	215	1200	32381.5
	Wednesday	43	150	200	250	1200	24990
	Thursday	50	114	152	190	1200	29834
	Friday	38	138	184	230	1200	32523
	Saturday	46	150	200	250	700	1170
	Sunday	50	0	0	0	240	195
	Sum	302	789	1052	1315	155861.5	

Table 2. Simulated annealing results

First time	Second time	Third time	Fourth time	Fifth time	Sixth time	Seventh time	Total cost
67	77	83	91	113	174	193	5594453

In this paper, will compare the results of all three models and find that model 1 achieves low cost in the scenario of stable demand and flexible production line by optimizing production scheduling and inventory management. Model 2 is suitable for complex environment where component processing takes a long time due to the increase of cost caused by new time constraints. Although the short-term cost of Model 3 is high, it guarantees the continuity of production through equipment maintenance, which is in line with equipment-intensive production. Different models have their own advantages and disadvantages in dealing with sudden demand and market changes. It can be seen that selecting the adaptation model based on actual production and market demand is the key to improving the competitiveness of enterprises. In the future, will use specific cases to analyze how model 2 can achieve demand forecasting and production adjustment with historical data when dealing with external uncertain demand.

In this paper, have deeply discussed the theoretical construction and solution of different production models, as well as their optimization capabilities under specific production constraints and equipment maintenance requirements. Continuing our exploration of the production planning optimization process, this section will show the application effect of Model 2 through a practical case, especially in the complex environment where external demand is unknown, how to use historical data to predict future demand and optimize assembly production planning accordingly. In this paper, will use the autoregressive (AR) time series model[11]to process historical order data to demonstrate the practical value of statistical modeling methods in improving the real-time response capability and prediction accuracy of production plans.

In this case study, face the common challenges of demand forecasting. The 70% of the historical order data is used as a training set to establish and adjust the time series model, and the remaining 30% is used as a test set to evaluate the predictive ability of the model. The application of this method will not only enhance the adaptability and response speed of the production plan, but also significantly improve the utilization efficiency of resources and meet customer expectations. The case analysis in this chapter will specifically demonstrate the application of statistical modeling in actual business decision-making, especially in demand forecasting and production adjustment.

The solution of the AR time series prediction model : the data of the first 27 weeks are used as the training set, and the data of the last 3 weeks are used as the test set. The relationship between the statistics T, rank correlation coefficient qs, maximum relative error and the order P of AR time series model is shown in table 3.

Table 3. Relationship between time series order and maximum relative error

Model order P	1	2	3	4	5	6	7
Statistic T	2.1316	2.1316	2.1316	2.1316	2.1316	2.1316	2.1316
Rank correlation coefficient qs	0.406	0.406	0.406	0.406	0.406	0.406	0.406
Maximum relative error	14.80%	13.40%	13.70%	10.70%	12.5%	8.13%	9.01%

It can be seen from Table 3 that qs > 0, T is greater than the critical value of t distribution with a significant level of 0.1, and the model is stable. When the AR time series factorial is selected as 6, the maximum error of daily demand is 8.13%, less than 10%, which meets the requirements. Therefore, in this paper, finally choose the autoregressive model AR(6) to predict the daily demand D_t:

$$D_t = 0.1567D_{t-1} + 0.0066D_{t-2} + 0.2001D_{t-3} + 0.5187D_{t-4} - 0.1049D_{t-5} + 0.2499D_{t-6} + \varepsilon_t \quad (1)$$

At this time, the weekly demand error of the test set (after three weeks) is [0.022,0.025,0.006], which is far less than 15%, which meets the requirements. The daily predicted demand and actual demand data are shown in Figure 3:

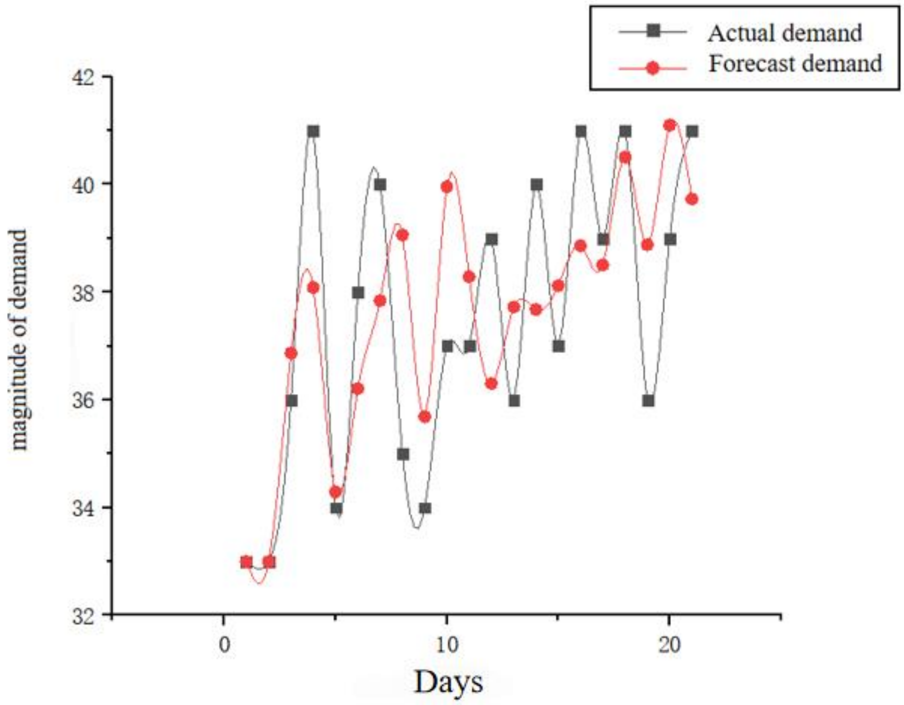

Figure 3. Daily forecasted vs. actual demand

The determination of the optimal assembly scheme : In this paper, bring the predicted demand into the improved model 2: the improved assembly system batch production planning model, and apply the heuristic algorithm based on network analysis dynamic programming to solve the problem. The following is the specific results of the optimized production plan and related costs :Tabie 4.

Table 4. Case study optimization results

Date	Forecast demand	WPCR assembly quantity	A assembly quantity	B assembly quantity	C assembly quantity	Production preparation costs	Inventory fees
Monday	42	42	204	272	340	1200	28348
Tuesday	39	68	129	172	215	1200	32440.5
Wednesday	42	43	150	200	250	1200	25015
Thursday	43	50	114	152	190	1200	29868
Friday	42	38	138	184	230	1200	32516
Saturday	42	46	150	200	250	700	1110
Sunday	44	50	0	0	0	240	215
Sum	294	337	1011	1348	1685	156452.5	

It can be seen from the above table that although the predicted demand fluctuates, our production plan can be adjusted in time to match the demand changes, thus maintaining a high delivery rate. Especially in the case of a sudden increase in demand, the number of production increases accordingly, showing the advantages of the model in terms of adaptability and responsiveness.

5. Conclusions

In this paper, aiming at the problems of scheduling efficiency, cost control, time constraint adaptation and equipment maintenance optimization in intelligent robot water pipe cleaning production, construct a three-layer capacity-constrained batch production model, an improved time constraint model and an equipment maintenance optimization model, and carry out case analysis with AR time series model. The dynamic programming heuristic algorithm is used to balance the availability and cost of components, and the genetic algorithm is used to improve the adaptability of production plan to time constraints. The 0-1 integer variable and simulated annealing method are used to optimize the equipment maintenance and upgrading strategy, and the demand forecasting and production model are deeply integrated. The results show that the model significantly reduces the inventory cost and delay loss, the equipment maintenance strategy effectively guarantees the production continuity, and the coordination of demand forecasting and production scheduling improves the market response ability of the system. The reliability and superiority of the model under complex production constraints are verified, which can provide a systematic optimization scheme for the production process. The research results not only provide a feasible solution for the intelligent robot water pipe cleaning production system, but also its methodology and model framework can be extended to similar manufacturing systems, providing an important reference for production decision-making and theoretical research in related fields.Future research may focus on integrating the models with IIoT and digital twin for real-time optimization and predictive maintenance, extending the framework to multi-robot collaboration and dynamic scheduling under uncertain demands, and combining adaptive machine learning for real-time disruption handling. These efforts will drive smarter, more resilient, and sustainable manufacturing ecosystems.

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