Application of Improved Genetic Algorithm in Heat Treatment Production Line of Aviation Manufacturing Enterprises

Yuning Wang[1,a*], Daye Xie[2,a], Cong Suo[3,a], Qingyang Jiao[4,a], Mingang Yin[5,b]

wyn20090101@163.com[1]*, xdy@163.com[2], sc@163.com[3], jqy@163.com[4], yinmingang@163.com[5]

Engineering Technology Center, 1 Lingbei Street, Shenyang, China[a]
School of mechanical engineering, 111 Shenliao West Road, Shenyang, China[b]

Abstract. In response to the problem of high production volume and complex variable space in heat treatment production lines, such as KPI indicators (including production volume, maintenance cost, production line cycle, waiting time, equipment utilization rate, etc.), this paper establishes targeted optimization objective functions and constraint functions for different products using the NSGA2 genetic algorithm based on the equivalent agent model. By comparing and analyzing the optimization results under different conditions, the optimal maintenance strategy for the heat treatment production line was obtained.

Keywords: optimization, NSGA2, simulation, treatment production line

1 Introduction

In order to tap into the maximum production potential of production lines, aviation manufacturing enterprises need to spend a lot of funds and introduce the latest technology to transform existing production lines. They must master powerful tools to optimize the process flow, so that the production lines can operate low-cost, time-saving, efficient, and flexible. Digital simulation is such a powerful tool that can be used to analyze and evaluate various related factors before the production system and improved process flow are put into actual operation. With the emergence and rapid development of digital simulation technology, applying simulation technology to facility planning, design, analysis, and verification in enterprises can dynamically simulate the production and manufacturing process of products, without consuming any real manufacturing resources, predict the status of manufacturing systems, and make forward-looking decisions and optimize implementation plans[1]. Therefore, it is widely used in the design, scheduling, and planning of complex manufacturing systems, Further utilize industrial simulation methods to digitize and simulate optimization strategies, in order to verify their effectiveness and overcome the difficulty of considering complex production systems in detail and comprehensiveness in the past. For heat treatment production lines with multiple varieties, small batches, and numerous influencing factors in aviation manufacturing enterprises, in order to achieve comprehensive planning and systematic analysis of the production line, fully tap into the maximum potential of the production system constructed by factors such as personnel, equipment, materials, process flow, and production conditions, an advanced algorithm is needed to optimize the production system model and

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control its strategy. Ni Qianyun conducted research on multimodal RCPSP based on improved genetic algorithm, and designed a new genetic algorithm - LPSGA - to solve the mathematical model of total project duration[2]. Xu Junhao applied the six point fuzzy number operation and comparison method, and improved the genetic algorithm by combining the two to solve the multi resource constrained project scheduling problem[3]. Zhou Yaqin adopted a nested ant colony genetic hybrid algorithm to solve the dual resource constrained production scheduling problem of aerospace structural components in three different resource dimensions[4]. Shi Fei simulates the research problem and ultimately forms a method that can optimize the objectives. During the search process, it is able to actively and adaptively collect and accumulate relevant information, and adaptively determine whether the searched solution is the optimal solution[5]. Based on the research achievements of these predecessors and the current research status of genetic algorithms, this article adopts NSGA2 for the optimization research of the objectives.

2 The basic principle and implementation of NSGA2 algorithm

Multi objective optimization algorithms are usually divided into two categories: traditional multi-objective optimization algorithms and multi-objective evolutionary algorithms.

2.1 Traditional multi-objective optimization algorithms

The traditional approach to solving multi-objective optimization algorithms is to first normalize multiple objective functions, and then use the weighted sum method to combine multiple objective functions into a single objective function. This transforms a complex multi-objective optimization problem into a simple single objective optimization problem, ultimately obtaining a subjective optimal solution[6].

2.2 Multi-objective evolutionary algorithm

Deb proposed the Non Inferior Graded Sorting Genetic Algorithm with Elite Strategy (NSGA-II), which can improve the convergence speed and maintain the diversity of results by adopting fast graded sorting and elite strategy. At present, the NSGA2 algorithm has become an excellent algorithm for solving multi-objective optimization problems and has been widely applied in engineering research and other fields. According to the analysis of the multi-objective mathematical model of the pipeline network, it is known that it is a class of discrete high-dimensional combinatorial optimization problems, and also a multi-objective optimization problem composed of economy and reliability. Traditional optimization methods are not suitable for solving such problems, so the classic NSGA2 algorithm was selected[7].

2.3 Implementation of NSGA2 algorithm

The parent population P_t generates a temporary optimal population through a tournament mechanism, and then performs crossover and mutation operations on the optimal population to generate a offspring population R_t. The parent population and offspring population R_t are reorganized into a population size of $2N$. These $2N$ individuals are divided into i non dominated frontiers through fast non dominated sorting, and finally, the diversity of the population is maintained through the calculation of crowding distance. The overall idea of the NSGA2 algorithm is shown in **Figures 1**.

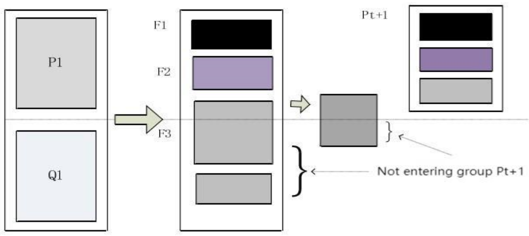

Fig. 1. The idea of NSGA2 algorithm.

3 Research on Improvement of NSGA2 Algorithm

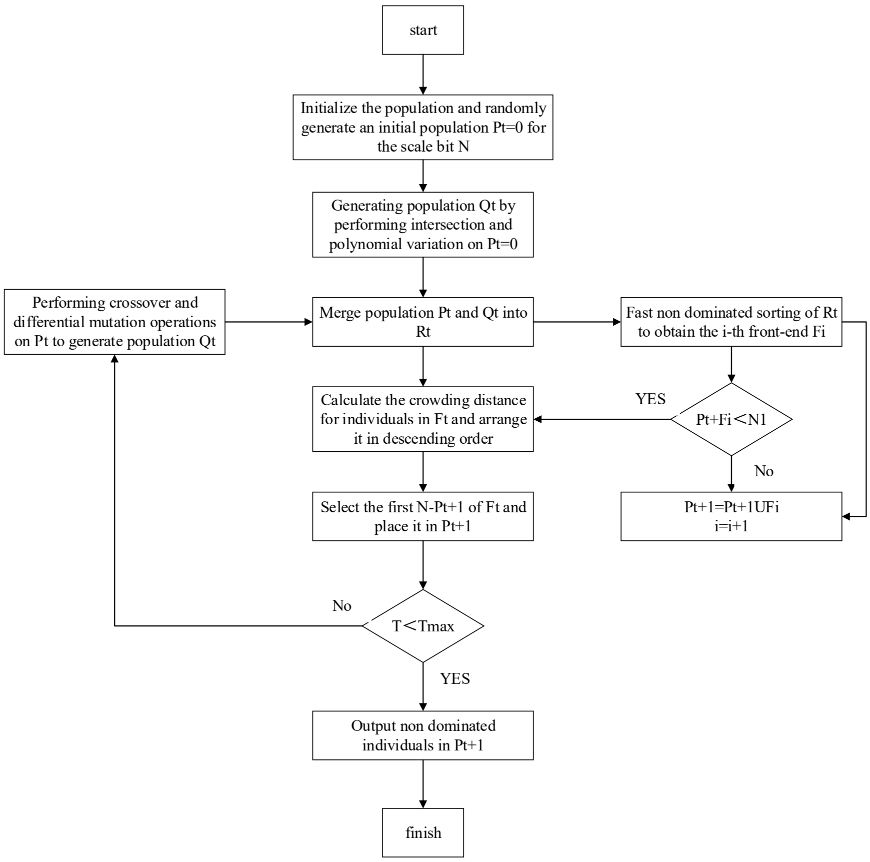

Fig. 2. The flowchart of NSGA2 algorithm.

Through extensive research, we have found that the NSGA2 algorithm, based on the crowding distance mechanism, also has certain shortcomings in maintaining population diversity, because judging individual distribution performance solely from the size of crowding distance has limitations. There is an easily overlooked issue here: the density of individuals and the crowding distance between individuals are not consistent, but many people have this misconception that individuals with larger crowding distances have higher density[8-10]. This will result in some individuals with high solution density and crowded distances being retained, leading to uneven distribution of the obtained solutions and easy trapping in local optima. The flowchart of the NSGA2 algorithm is shown in **Figure 2**.

3.1 Introduction of differential mutation strategy

Since its proposal, DE has shown strong advantages in dealing with many problems, because the unique differential mutation operator of DE algorithm can cause disturbance to the evolutionary direction of individuals in the population. For the initial population P, a parent individual P1 is randomly selected, and its temporary offspring individual P2 is generated by the following mutation operator. The DE/current to best/1/bin differential mutation strategy can be expressed as equation (1) .

$$V_i^{t+1} = X_i^t + F_1\left(X_{\text{best}}^t - X_i^t\right) + F_2\left(X_{r1}^t - X_{r2}^t\right) \tag{1}$$

V_i^{t+1} is the differentially mutated individual, X_i^t is the parent individual, X_{best}^t is the selected optimal individual for the current population, X_{r1}^t and X_{r2}^t are two randomly selected parent individuals from the population to increase population diversity.

3.2 Introduction of differential mutation strategy

F_1 and F_2 are two uncertain factors, which are mostly artificially set. Because the efficiency of the NSGA2 algorithm is relatively low, when using it to solve multi-objective optimization problems, it is hoped to accelerate the search speed of the algorithm in the early stage, and then strengthen the local search ability in the second half of the search. Therefore, a linear real-time adjustment of the scaling factors F_1 and F_2 based on evolutionary algebra is proposed, defined as equation (2) .

$$\begin{aligned} F_1 &= F_{\max} - \left(F_{\max} - F_{\min}\right) t / T \\ F_2 &= F_{\max} + \left(F_{\max} - F_{\min}\right) t / T \end{aligned} \tag{2}$$

3.3 Performance testing of NSGA2 algorithm

In order to test the performance of the proposed improved NSGA2 algorithm, we selected four classic ZDT series test functions that are most commonly used in the field of multi-objective optimization, and programmed them using MATLAB. The program ran on a CPU environment of 4GB of memory and 2.4G of main frequency.

4 Application Example of Heat Treatment Production Line

Using industrial simulation tool plant simulation for logical modeling,the current production layout of a heat treatment production line is shown in **Figure 3**.

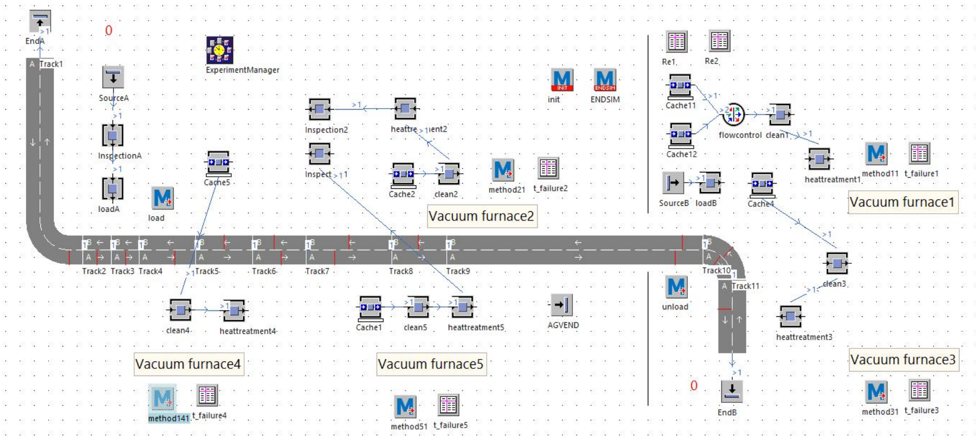

Fig. 3. Industrial Simulation Model for Heat Treatment Production Line.

The heat treatment production line includes two types of products, A and B. The preventive maintenance interval corresponding to each fault mode in the production line is defined as the optimization variable, and the objective function is a comprehensive model of the output and maintenance cost of the two products.

The yield of the product was optimized using single objective optimization methods, as shown in **Figure 4.**

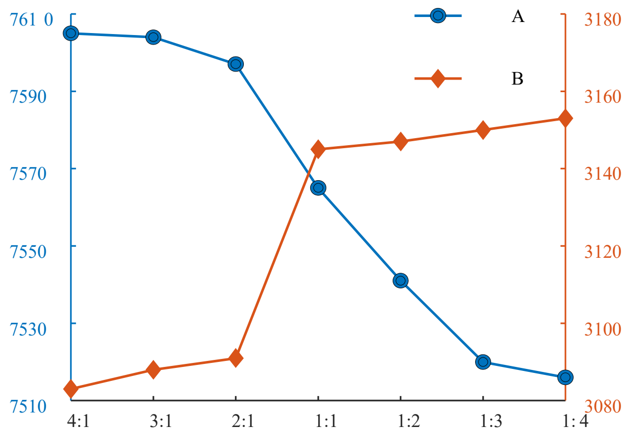

Fig. 4. Single objective optimization of product yield trends.

Similarly, the results obtained by using multi-objective optimization methods are shown in **Figure 5.**

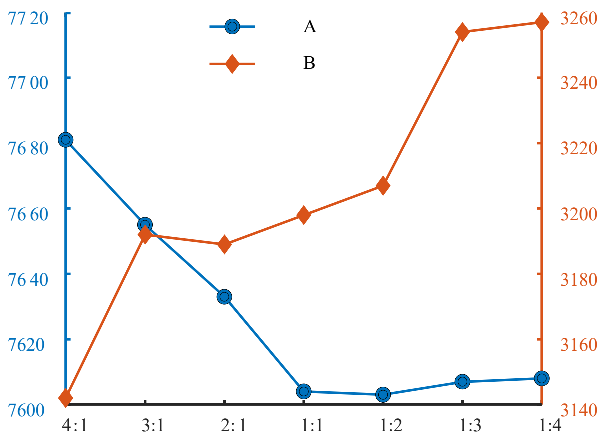

Fig. 5. Multi objective optimization of product yield trends.

Comparing Figures 4 and 5, it can be seen that regardless of the optimization results used for preventive maintenance of the heat treatment production line, the output of products A and B is higher than the original maintenance plan.

5 Conclusions

Aiming at the heat treatment production line, an improved genetic algorithm was used to optimize the parameters of the surrogate model, and simulation optimization tests were conducted on the Plant Simulation model of the production line based on the optimization parameters of different schemes. This method provides a solid theoretical foundation for the optimization of actual production lines, and offers different optimization plans for leadership goal decision-making. The optimization results can guide the actual production line to improve production capacity.

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