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Production Scheduling Optimization during Thermoforming of Ring Forgings Based on Genetic Algorithms

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Abstract: In the aerospace industry, many important components are made of ring forgings with characteristics of multi-variety and multi-batch. Such components have many steps and complex parameters in the thermoforming process. The process orders are dynamic and time-varying, and, thus, optimizing the total production time and energy consumption is difficult. To solve the mentioned troublesome and time-consuming problem, this work transformed the workpiece's required heating temperature and time index into the furnace temperature change and holding time index. Based on a genetic algorithm, an integrated production scheduling optimization of ring forging heating and model forming was established. The genetic algorithm for model improvement was optimized. The optimization objective was changed by using different fitness calculation methods. A multi-time simulation algorithm was designed to calculate each heating furnace's time and furnace temperature. The proposed optimization method was used for a thermoforming process of ring forgings. When the optimization objective was designed to consider energy consumption and time consumption comprehensively, the average time saving was 6.93%, and the average energy saving was 12.99%. When the optimization objective was designed to prioritize energy consumption, the average time saving was 3.89%, and the average energy saving was 16.53%. When the optimization objective was designed to prioritize time consumption, the average time saving was 10.35%, and the average energy saving was 10.63%. Using the scheduling results for production, compared with the practical factory data, the errors in the simulation time and energy consumption were 2.4% and 1.6%. The results show that the scheduling efficiency of integrated thermoforming production is significantly improved by using this optimization model, and the simulation results have high reliability. The energy consumption of orders is greatly reduced, and the total production time is greatly shortened.

Keywords: production scheduling optimization; thermoforming; ring forgings; genetic algorithm; multi-objective optimization; multi-time simulation

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1. Introduction

The forging industry is an essential industry with high energy consumption and huge orders. It is highly irreplaceable and essential in various fields. The forging process is of great significance to the light weight of automobile and aerospace components [1–4]. The forging process requires high metal temperatures. A heating furnace is commonly used to heat workpieces. In the actual process of production, the processing sequence of workpieces is seldom considered. This causes the heating furnace to be repeatedly heated to a high temperature and wastes a lot of energy. This is the main reason for the low energy utilization rate in the forging industry. According to a survey, each ton of forging consumes

0.8–1.2 tons of coal, which costs 150–250 dollars [5,6]. Its energy consumption accounts for about 25% of the total energy consumption of the machinery industry and about 75% of the total fuel consumption of various factories. The main problem behind low energy utilization rates is the lack of production technology management and energy-saving measures.

In the field of aerospace, there are a large number of different kinds of forgings. The production process of each forging is quite different. However, the demand for each forging is small. At the same time, the types of forgings required by different orders are quite different [7]. Because the demand for each variety is low and the heating and forging processes are easily confused, each type needs to be heated and forged separately and cannot be mixed. In the production process, if scheduling optimization is not carried out, the energy waste will be highly alarming. The production cost and production time will be significantly increased. Therefore, scheduling order workpieces is extremely important in this field. With the progress of industry, the manufacturing process will be more intelligent, and the production process of ring forgings will be more efficient [8,9].

Figure 1 shows the manufacturing process of ring forgings. The main energy-consuming and time-consuming process is the heating step. In the process of forging, in order to prevent the forging from being damaged, it is necessary always to keep the forging in a high-temperature range. It takes a lot of energy and time to heat forgings to the required temperature. At the same time, in order to ensure the consistent forgeability of all parts of the forgings, it is necessary to maintain the temperature for a specific time after reaching the required temperature. If the production scheduling optimization effect is not ideal, it will cause a tremendous waste of energy.

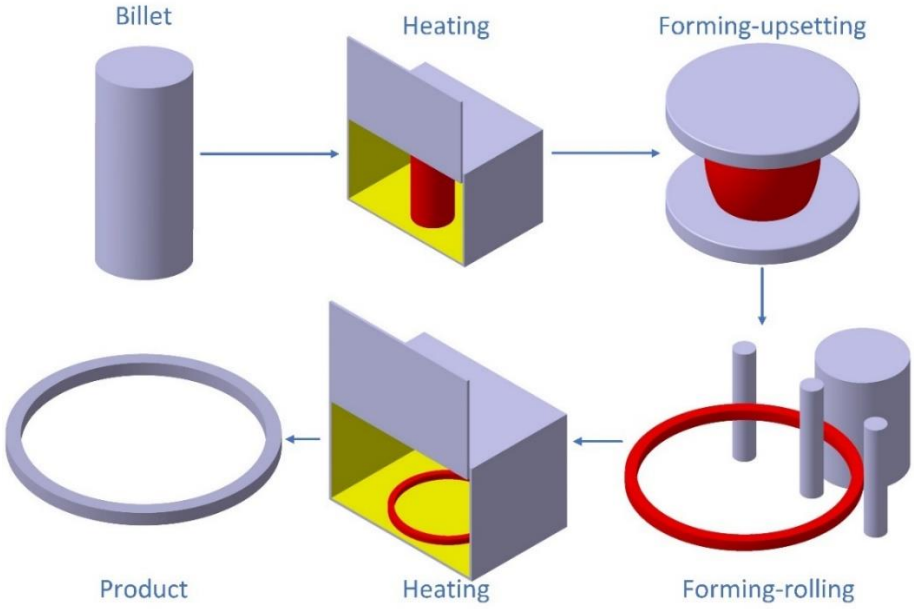

Figure 1. Schematic diagram of ring forging production process.

Usually, the scheduling of orders is generally divided into the production and the energy systems. Scheduling production of ring forgings should be regarded as a bilevel problem [10]. For general industrial production, the scheduling goal is set to reduce the idle assembly line time [11–13]. However, the energy consumption in the forging process should also be considered. For actual forgings, it can be divided into two types: separate heating and mixed heating. Separate heating means that only one workpiece can be placed in the heating furnace at the same time. Mixed heating means that multiple workpieces can be placed simultaneously in the heating furnace. In recent years, most research on production scheduling optimization has focused on mixed heating. Jiang et al. [14] used a genetic algorithm to schedule and optimize the production scheduling process. They tried to reduce the free space of the heating furnace. It had a good optimization effect on energy

consumption. Liu et al. [15] optimized for continuous and batch mixed production modes, formulating new rules to determine the optimal manufacturing sequence. Cheng et al. [16] established an energy-saving scheduling model to recycle the waste heat of the heating furnace and improve the energy utilization rate. Caldeira et al. [17] proposed a simulation optimization method composed of the Jaya algorithm, meta-heuristic algorithm, and Monte Carlo simulation to minimize the expected manufacturing time for the stochastic flexible job shop scheduling problem. Although the above research works showed good optimization effects, they are not suitable for separate heating forgings. He et al. [18] aimed at the heating furnace's maximum loading capacity to improve the heating furnace's utilization rate. Still, they did not consider the energy consumption caused by replacing different workpieces. Two scientific articles [19,20] used an exact algorithm to solve the scheduling optimization problem, but the total time required for optimization was longer when the number of orders was large. In other scientific articles [21–23], researchers used a heuristic algorithm to optimize the workshop scheduling problem. Still, the heuristic algorithm is a suggested optimization method; its final solution is only a better solution, and the overall optimization effect is poor. Wen et al. [24] used the NSGAII algorithm to reschedule machine failure dynamic scheduling problems. In view of the existence of order deadlines, Peng et al. [25] proposed a multi-agent genetic algorithm (MAGATS) based on tabu search to optimize scheduling in the presence of order deadline constraints. This method has a good optimization effect for mass forgings, but the optimization effect for ring forgings is poor. Palmer et al. [26] designed a scheduling optimization algorithm based on a simulated annealing algorithm, which has a broad target range and a poor optimization effect for special workpieces such as ring forgings. Moon et al. [27] proposed an optimization method for different electronic devices in processing plants based on a genetic algorithm. The optimization effect was good, but it was not suitable for the energy-saving process of forging production. Guo et al. [28] used a particle swarm optimization algorithm to schedule and optimize the production process. Kolisch et al. [29] proposed three different heuristic algorithms to maximize production efficiency on the assembly line. Chen et al. [30] optimized the production scheduling on the manufacturer's production line based on a genetic algorithm, reducing the idle time of the production line. Shao et al. [31] improved a genetic algorithm to make the production process more compact. However, none of the above four methods could optimize the overall energy consumption of the order. Based on the Lagrangian relaxation method, Czerwinski et al. [32] optimized the scheduling of different materials required by individual parts in the workshop, reducing the energy consumption and time consumption of producing a single piece. Still, this did not extend to all orders. Currently, the leading research on scheduling optimization is less concerned with different types of workpieces and more focused on maximizing the use of furnace space to process more workpieces. In terms of optimization objectives, most research has set the optimization objectives to save the time of order consumption. Few research works have focused on optimizing order time and energy consumption simultaneously.

This work focuses on solving the scheduling optimization problem of multi-variety variable batch ring forgings, mainly including:

1.1. Multiple Temperature Requirements

In the production process of aerospace and other transportation fields, there is a multi-variety of ring forgings, and the number of ring forgings of a single type is small. However, the heating and forming temperature of each ring forging is relatively high, and to avoid confusion, different types of forgings are not allowed to be heated in the same furnace simultaneously. If production scheduling optimization is not carried out, the production process will be time-consuming and energy-intensive. This work summarizes the process requirements of ring forgings, which mainly include the following characteristics:

(1) Due to the inconsistent physical properties of different materials, different types of forgings have additional requirements for furnace entry temperature and holding temperature. The furnace entry temperature is usually required to be lower than a

specific temperature value, and the holding temperature is usually another temperature value higher than the maximum furnace entry temperature. No matter how the overall algorithm is optimized, the difference between the maximum furnace entry temperature and the holding temperature of ring forgings cannot be reduced. Thus, the general algorithm should focus on optimizing the rest.

(2) After the temperature of the ring forging rises to the holding temperature, it needs to be insulated to eliminate the internal stress of the material. There are the shortest and the longest holding times in the production of ring forgings. When the temperature of the ring forgings rises to the holding temperature, the ring rolling operation needs to be held for a corresponding period of time. The actual holding time is any value between the shortest and longest holding times. As the holding temperature is higher, making the holding time shorter can save a lot of energy.

(3) The ring forging process requires high plastic behavior of the workpiece, and the plastic behavior of the workpiece is closely related to the temperature [33]. For the ring forgings considered in this work, the plastic behavior increases with the rise in temperature. When the workpiece temperature is lower than the final forging temperature, the workpiece must be returned to the heating furnace for heating to prevent the workpiece from being damaged during ring rolling. Suppose the workpiece is returned to the heating furnace. In that case, the furnace temperature of the heating furnace needs to be raised to the workpiece holding temperature and re-insulated, which consumes a lot of energy. Usually, the workpiece temperature is too low because the workpiece is taken out of the heating furnace in advance. The workpiece is placed in the air for too long before the ring rolling is performed. Thus, optimizing the scheduling of the workpiece production process can avoid this situation and save a lot of energy.

(4) The overall manufacturing process of most ring forgings requires multiple heating and ring rolling processes, and the specific temperature and holding time requirements are different each time. The process sequence of ring forgings cannot be changed. If there are multiple heating and ring rolling operations, they must be carried out in sequence according to the process manual. Suppose the temperature of the workpiece after ring rolling is higher than its maximum furnace entry temperature. In that case, it is necessary to wait for the workpiece temperature to decrease naturally. After its temperature is lower than the maximum furnace entry temperature, subsequent heating operations can be performed.

1.2. Multi-Heating Furnace Coordination

In actual factory production, the number of heating furnaces is usually large, and different heating furnaces operate independently of each other and do not interfere with each other. To correctly allocate the various operations of each heating furnace, it is necessary to unify the temperature changes of different levels of power consumption of the heating furnaces, that is, normalizing the change in furnace temperature into several specific modes. The temperature of the heating furnace should not be higher than the maximum temperature of the workpiece when the workpiece is placed in the furnace. After the workpiece is placed, the temperature should be quickly raised to the workpiece holding temperature. The actual holding time of the workpiece must be within the range of the holding time required by the workpiece, and it cannot be too long or too short. To avoid confusion, the same heating furnace only heats one workpiece at the same time to prevent possible mistakes in the actual production process.

To solve the above problems, this work proposes an optimization scheme for ring forging production scheduling based on a genetic algorithm, which transforms the process requirements of ring forgings into restrictions on heating furnaces. It sets independent time parameters for each heating furnace. This method can realize the multi-parameter simulation calculation of the order production process of different heating furnaces and

adjust the fitness ratio of the genetic algorithm, which overcomes the optimization difficulty caused by the different process requirements of varying ring forgings in actual production.

2. Production Scheduling Model for Ring Forging Thermoforming

2.1. Artifact Model

To facilitate the subsequent algorithm scheduling, a workpiece process demand model is established in which the temperature and time required to process the workpiece is recorded. The entry temperature and holding temperature of the workpiece are equivalent to the furnace temperature change. Usually, ring forgings require a furnace temperature lower than a specific temperature value. The holding temperature is a particular value and is higher than the temperature of entry into the furnace. To ensure maximum efficiency, the furnace entry temperature is set to the highest furnace entry temperature required by the forging. It is ensured that the energy required for the forging to rise to the holding temperature is as little as possible. At the end of the heat preservation of the workpiece, the ring rolling operation is directly carried out to prevent it from being placed in the heating furnace for too long. The furnace temperature at the time of discharge is the holding temperature. At the same time, when a workpiece has multiple heating steps, an array is set to store the number of steps for each workpiece. When each step of heating is set, it is verified whether the workpiece's pre-step is completed. For each step of each workpiece, its model parameters are shown in Table 1:

Table 1. Artifact model parameters.

Parameters	Meanings
tem_{in}	The temperature of the workpiece on entry into the furnace, that is, at what temperature the workpiece can be placed in the furnace.
tem_{out}	The workpiece release temperature, that is, the workpiece holding temperature.
$Time_{in}$	The total heating time of the workpiece; its value includes the time from the furnace temperature to the holding temperature and the holding time.
num_{in}	The total number of steps in the workpiece, that is, the workpiece consists of several steps in sequential order.

Then, for each workpiece, its actual data consist of the above data. Each dataset consists of a total number of steps of a workpiece, num_{in}, and num_{in} sets of $[tem_{in}, tem_{out}, Time_{in}]$ data.

2.2. Heating Furnace Model

The main goal of the furnace model is to map the power consumption of the furnace to temperature changes. In the actual production process, if the total production time is to be the shortest, then, ideally, there should be only three working states of the heating furnace: namely, the maximum power working heating state, the temperature maintaining state, and the minimum power working cooling state. During the heating process, the furnace temperature of the heating furnace will be higher than the ambient temperature. Thus, the heating furnace will always radiate heat to the surrounding environment. For the heating furnace, its heat dissipation power at any moment is:

$$P_d = h_d A_d (T_{now} - T_0) \tag{1}$$

In the equation, h_d is the sum of the convection heat transfer coefficient and radiation heat transfer coefficient of the heating furnace; A_d is the heat dissipation area of the heating furnace; T_{now} is the furnace temperature of the heating furnace; and T_0 is the ambient temperature.

Then, at every moment, the actual power in the heating furnace is:

$$Q = P_{now} - P_d \tag{2}$$

In the equation, Q represents the change in thermal energy per unit time, and P_{now} represents the heating power of the heating furnace per unit time.

Then, the temperature change ΔT is calculated as follows:

$$\Delta T = \frac{Q}{mc} \tag{3}$$

In the equation, m represents the air quality in the furnace, and c represents the air-specific heat capacity.

Then, for the three working states, the temperature change parameters are shown in Table 2:

Table 2. Furnace model parameters.

Parameters	Meanings
$tem_{increase} = \frac{P_{max} - P_d}{mc}$	The number of temperature rises per unit time of the heating furnace when working in the maximum power state.
$tem_{drop} = \frac{P_d}{mc}$	The number of temperature drops per unit time of the heating furnace in the cooling working state.
$P_{keep} = h_d A_d (T_{now} - T_0)$	Heating furnace power in heat preservation working state.

Obviously, the power consumption in the heating and cooling working states of the furnace is P_{max} and 0, respectively. Then, according to the above modeling, the temperature change relationship of the heating furnace can be obtained.

2.3. Ring Rolling Mill Model

The ring rolling process is a forming process in the production process of ring forgings. The workpiece is not heated, and the energy consumption is negligible compared with the heating process. The time that it consumes is generally between 10 and 30 min, and its time impact on the overall process is negligible compared to the time consumed by the heating process. The most significant impact of the ring rolling process on the production process is that when there is no idle ring rolling machine, the workpiece needs to be kept warm to wait for an idle ring rolling machine. Its parameter is:

$T_{wave} = (time_1, time_2, \ldots, time_k)$, which is the floating value of the holding time caused by waiting for the ring rolling in each process. In general, its value is 0. If the process needs to wait for the ring rolling machine to be vacated, its value will rise accordingly.

2.4. Objective Function

According to the above model, the heating furnace and sequence corresponding to all steps of each workpiece are finally solved, and the relevant parameters are shown in Table 3:

Table 3. Objective function parameters.

Parameters	Meanings
$sort = (i_1, i_2, i_3, \ldots, i_k)$	The heating sequence of each heating step of each workpiece is collected, and its number is equal to the total number num_{in} of steps. Among them, the heating sequences of each heating furnace are independent of each other.
$choose = (tot_1, tot_2, tot_3, \ldots, tot_k)$	The number of heating furnaces selected for each step, the number of which is equal to the total number of steps num_{in}.
$W_{count} = \sum W_{each}$	The total power consumption; its value is the sum of the power consumption of all connection segments.
$T_{count} = max(T_{each})$	Total time, the maximum value of all furnace completion times.
$fitness$	Individual fitness, the value of which indicates the superiority of the individual.

3. Genetic Algorithm

According to the characteristics of the problem and the various requirements in the model, it is necessary to optimize the production scheduling of the workpiece, that is, to solve the optimal set of *sort* and *choose*. According to the characteristics of this problem, a genetic algorithm is selected as the main optimization algorithm. At the same time, according to the characteristics of the problem, the process of the genetic algorithm is modified to make it fit the requirements of this work. The flow of the genetic algorithm is shown in Figure 2.

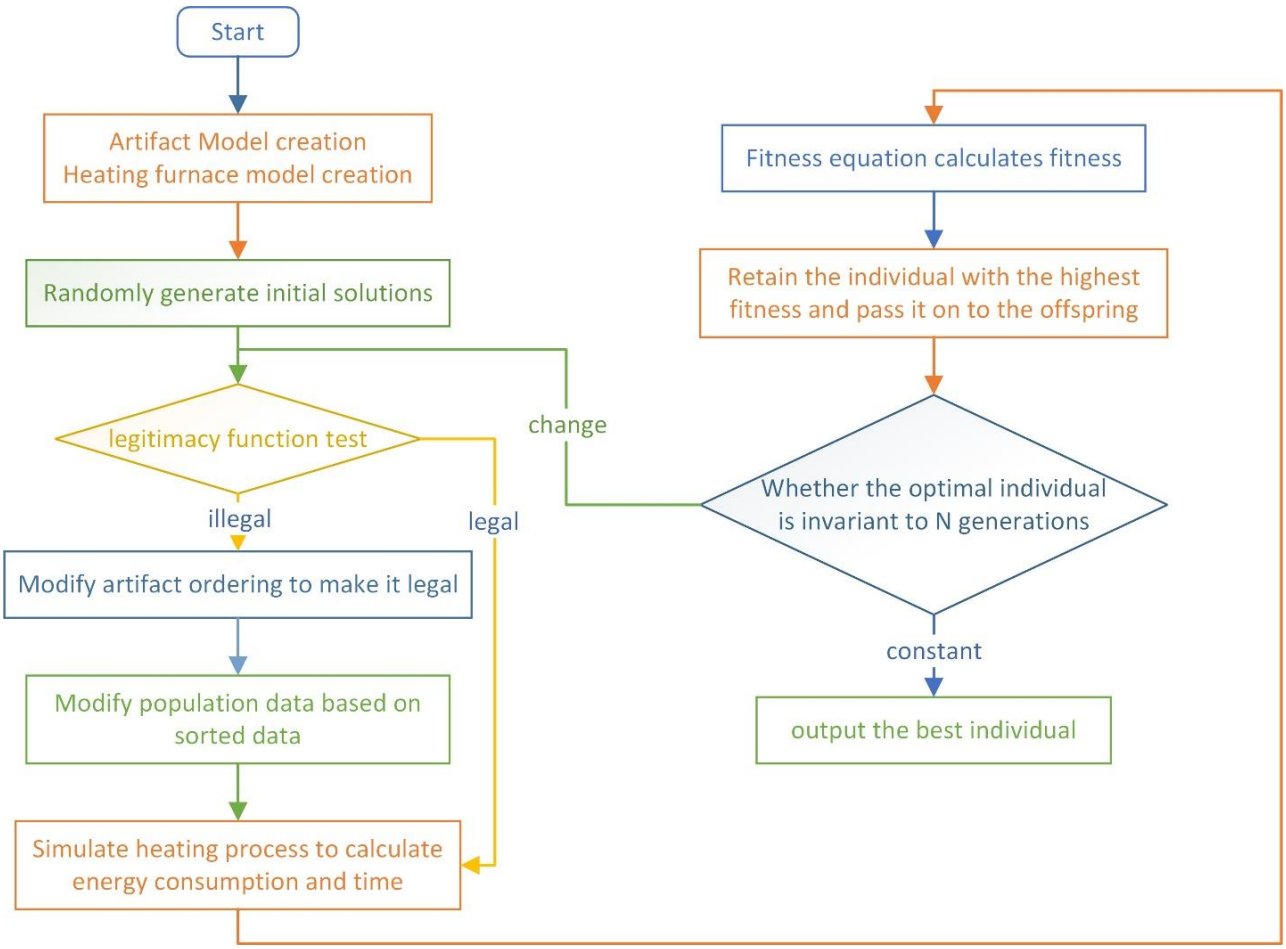

Figure 2. Schematic diagram of scheduling optimization analysis process based on genetic algorithm.

3.1. Basic Steps of the Algorithm

In this work, the genetic algorithm is used for overall optimization, and the specific steps are as follows:

Step 1: Randomly generate N initial solutions to form the initial population pop_{this}, where N represents the population size.

Step 2: Make a legitimacy modification to each individual and modify the stored value in the population according to the modified individual.

Step 3: Simulate the heating process to calculate the total power consumption and total time.

Step 4: Import the total power consumption and total time into the fitness equation to calculate the fitness value $fitness$ and directly retain the individual with the highest fitness to the next generation.

Step 5: According to the proportion of individual fitness, select the parent individually to generate offspring and use crossover and mutation to fill the offspring population pop_{next} according to the probability.

Step 6: Judge whether the optimal solution of continuous C generation remains unchanged. If it is not satisfied, go to Step 2; if it is satisfied, output the optimal solution as the final optimization solution.

3.2. Generation of the Initial Solution

It can be known from the model that each individual in the population stores the furnace and the sequence selected for the workpiece. Then, when the initial solution is generated, the process steps and sequence of heating in each furnace are generated, respectively. A parameter flag is set up to record whether each process has been assigned a furnace sequence. After each process is allocated, it will be recorded in flag correspondingly. The process that has been recorded by flag is the process that has been processed. If there are m furnaces and n process steps in total, then m cycles will be carried out. Each cycle randomly generates the total number of steps $rand_{in}$ heated by the heating furnace and generates $rand_{in}$ different numbers between [1,n], which is the sequence of the heating process of the heating furnace. If the corresponding generation craft has already been allocated, the sequence is re-generated. Finally, the furnace number and process sequence are recorded in choose and sort, respectively. The steps are repeated to fill pop_{this}, which is the initial population.

3.3. Calculation of Fitness Parameters

The fitness function is the degree of adaptation of an individual to the living environment. The larger the value, the higher is the fitness of the individual to the environment, and the greater is the probability of survival and reproduction. As an essential basis for generating offspring, the calculation method of fitness greatly determines the characteristics of the final optimal solution. Different fitness calculation methods will eventually generate different optimal solutions. Since there are two parameters of power consumption and time during scheduling optimization, the calculation method of fitness can determine the proportion of the two.

3.4. Roulette Selection of Genetic Individuals

Individuals that can reproduce offspring will be selected based on fitness, and the selection method is a roulette algorithm. The fitness of all individuals is added up to obtain the total fitness, and the fitness proportion of each individual is calculated. Then, the fitness proportion is:

$$fitness_{percent} = \frac{fitness}{\sum fitness} \tag{4}$$

From the fitness ratio, the fitness roulette can be obtained. Figure 3 shows an example data fitness roulette. According to the fitness roulette, each region corresponds to different individuals. A value is randomly generated within the range of $[0, 1]$, and which area in the fitness roulette it belongs to is calculated. Its corresponding individual is the individual finally selected by the roulette algorithm.

3.5. Inheritance to Obtain Offspring

In the genetic algorithm, an important way of population evolution is to obtain offspring according to the individual genetics of the current generation. The general methods of inheritance are crossover, mutation, and direct inheritance. The genetic marker parameters $rand_{cross}$ and $rand_{var}$ are set to represent the probability of crossover and mutation. At inheritance, a genetic marker parameter $rand_{pop}$ within the range $[0, 1]$ is generated. If there are k furnaces and n processes in total, then:

(1) If $rand_{pop} < rand_{cross}$, crossover to obtain offspring. Use the roulette algorithm to select individuals A and B of this generation. Randomly generate the number of intersections $rand_{num}$ within the range of $[0, n]$, and $rand_{num}$ indicates the number of processes to cross. Generate $rand_{num}$ values with different numbers in the range $[0, n]$. Crossover the corresponding numbered process sequences in A and B and count the two bodies after the crossover into the offspring.
(2) If $rand_{pop} < rand_{cross} + rand_{var}$, perform mutation operation. Use the roulette algorithm to select individual A of this generation. Randomly generate variation number within $rand_{num}$ range $[0, n]$, representing the number of processes to mutate, and generate $rand_{num}$ numbers with different values within $[0, n]$ range. Re-randomly generate the sequence of the corresponding numbers in A and put the mutated individuals into the offspring.
(3) If the above two equations are not satisfied, then direct inheritance. Use the roulette algorithm to select the individual A of this generation and put it directly into the offspring.

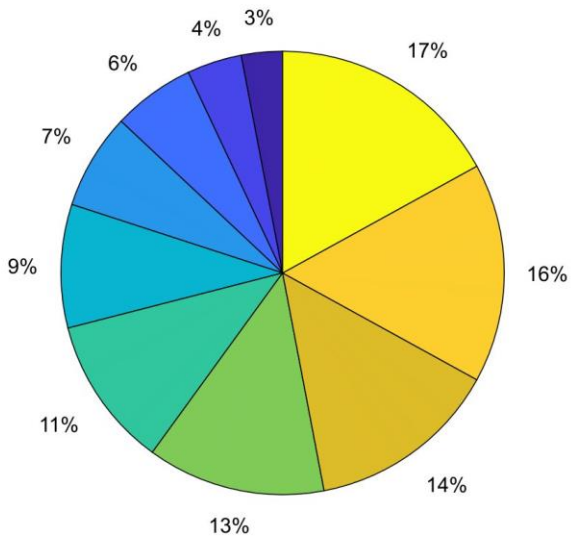

Figure 3. Fitness roulette wheel reflecting the proportion of individual fitness.

3.6. Legality Modification Simulation

In the actual order, there are multiple forging processes for each workpiece. When scheduling production, it is necessary to strictly follow its sequence. However, its order is not strictly followed when generating the initial population and multiplying the next generation. Thus, it is necessary to carry out preliminary simulations of individual data and analyze and revise their illegality.

According to the data stored in the individual, each process is archived in order of each heating furnace order $sort_{each}$. If multiple processes are in the same order, the workpieces with the same order will be randomly ordered again, and the subsequent workpieces will be moved backward in order. After the archive sorting is completed, if there is a vacant sorting, the subsequent workpieces will be advanced in turn to fill the vacancy.

According to the modified order $sort_{each}$, the heating process is simulated. The parameter now_{each} is set to store the sequence performed by each furnace. For each heating furnace, if the current process has no pre-step or the pre-step has been completed, the furnace can proceed to the next step and the process corresponding to this step is recorded as completed. If the pre-step is not completed, the heating furnace needs to wait for the pre-step to complete before proceeding to the next step. If all furnaces are waiting for the previous step to proceed, this means that the sequence cannot proceed and needs to be modified. A furnace is randomly selected; its current step is swapped with the previous step; and the simulation is continued after the swap. If the situation cannot be continued after the exchange, the exchange is performed again until all of the steps are simulated.

After the simulation is complete, the data in the individuals of the population are modified according to the modified ordering.

3.7. Calculation of Energy Consumption and Time

The time and energy consumed by the sorting can be simulated and calculated from the data that have been modified to ensure their pre-validation. The parameter $Time_{all}$ is set to record the current time of each heating furnace. The parameter tem_{all} is set to record the current temperature of each heating furnace and parameter $Time_{finish}$ to record the completion time of each heating process. The parameters $Time_{count}$ and W_{count} are set to record the total energy consumption of the individual sorting. With the whole time, $Time_{increase}$ and $Time_{keep}$, respectively, record the total heating time of the furnace with full power and the total holding time.

First, each process is archived in the order data $sort_{each}$ of each heating furnace. Then, the heating process of each heating furnace is simulated, respectively. In each simulation, each furnace tries to perform its current turn. If the process number is k, the state of the heating furnace is $i-1$ before the process is performed, and the state is i after the process is completed. Then, after the process is completed, the furnace temperature is:

$$tem_{all}[i] = tem_{out}[k] \tag{5}$$

(1) If the process has no pre-step, after the process is completed, the time change of the heating furnace is:

$$Time_{all}[i] = Time_{all}[i-1] + \frac{tem_{all}[i-1] - tem_{in}[k]}{tem_{change}} + Time_{in}[k] \tag{6}$$

In the equation, tem_{change} represents the change in temperature per unit of time. Thus, its value is:

$$tem_{change} = \begin{cases} tem_{increase}, tem_{all}[i-1] < tem_{in}[k] \\ tem_{drop}, tem_{all}[i-1] > tem_{in}[k] \end{cases} \tag{7}$$

Then, if the furnace temperature needs to be increased in order to handle this process, the $Time_{increase}$ value changes as:

$$Time_{increase} = Time_{increase} + \frac{tem_{all}[i-1] - tem_{in}[k]}{tem_{increase}} \tag{8}$$

(2) If there is a pre-step in the process, it needs to wait for the pre-step to be completed before performing this step. The relational equation for judging whether the pre-steps affect the process is:

$$Time_{finish}[k-1] - Time_{all}[i-1] <= \frac{tem_{all}[i-1] - tem_{in}[k]}{tem_{change}} \tag{9}$$

If Equation (9) is satisfied, the pre-steps will not affect the process, and the calculation can be performed according to Equations (6)–(8). If Equation (9) is not satisfied, this means that the pre-steps have a great influence on the production of the process. At the same time, it can be seen from Equation (9) that only when the heating furnace needs to wait for the completion of the workpiece does it need to be considered separately. Then, the heating and cooling of the heating furnace do not affect the time for finishing the process, and the heating furnace time changes as follows:

$$Time_{all}[i] = Time_{finish}[k-1] + Time_{in}[k] \tag{10}$$

Because the heating furnace needs to wait for the pre-processing to be completed to save energy, when the time allows the heating furnace to cool down to room temperature,

the heating furnace will naturally cool down to room temperature and heat up to the required temperature with full power before the workpiece is processed. When time does not allow, the heating furnace is set to cool down first and then keep warm or keep warm first and then heat up. Then, the judgment equation for whether time is allowed is:

$$Time_{finish}[k-1] - Time_{all}[i-1] > \frac{tem_{all}[i-1]}{tem_{drop}} + \frac{tem_{in}[i]}{tem_{increase}} \tag{11}$$

When the above equation is established, the change in $Time_{increase}$ is:

$$Time_{increase} = Time_{increase} + tem_{in}[k]/tem_{increase} \tag{12}$$

When the above equation is not established, if $tem_{all}[i-1] < tem_{in}[k]$, the heating time $\Delta Time_{increase}$ of the furnace for processing this process is:

$$\Delta Time_{increase} = \frac{tem_{in}[k] - tem_{all}[i-1]}{tem_{increase}} \tag{13}$$

Then, the holding time $Time_{keep}$ and the heating time $Time_{increase}$ are:

$$\begin{cases} Time_{increase} = Time_{increase} + \Delta Time_{increase} \\ Time_{keep} = Time_{keep} + Time_{finish}[k-1] - Time_{all}[i-1] \end{cases} \tag{14}$$

If $tem_{all}[i-1] >= tem_{in}[k]$, the cooling time $\Delta Time_{drop}$ of the furnace for processing this process is:

$$\Delta Time_{drop} = (tem_{all}[i-1] - tem_{in}[k])/tem_{drop} \tag{15}$$

Then, the holding time $Time_{keep}$ is:

$$Time_{keep} = Time_{keep} + Time_{finish}[k-1] - Time_{all}[i-1] \tag{16}$$

After the above treatment, the process that the heating furnace should deal with has been completed. After processing, the time when the workpiece is processed is recorded:

$$Time_{finish}[k] = Time_{all}[i] \tag{17}$$

Then, after all processes are completed, the total power consumption W_{count} and total time $Time_{count}$ of the sequence can be obtained:

$$\begin{cases} Time_{count} = max(Time_{all}) \\ W_{count} = Time_{increase} \cdot P_{max} + Time_{keep} \cdot P_{keep} \end{cases} \tag{18}$$

4. Results and Discussion

4.1. Comprehensive Target Optimization

In order to better allocate the power consumption and time ratio, the fitness calculation equation is set as:

$$fitness = Sigmoid(W_{exp} - W_{count}) + log\left(\frac{Time_{exp}}{Time_{all}}\right) \tag{19}$$

In the equation, W_{exp} and $Time_{exp}$ represent the expected value of power consumption and the expected value of time, respectively. The sigmoid function is defined as follows:

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \tag{20}$$

The fitness calculation method is more inclined to optimize time and power consumption when the time changes little. The optimization goal will be more comprehensive, considering both power consumption and time in the optimization results.

The simulation scheduling optimization is carried out according to the actual production data of a factory. The relative representative order data of the existing four batches are shown below, and the specific process requirements of each workpiece in batch 1 are shown in Table 4:

Table 4. Specific process requirements of batch 1.

Process Number	tem_{in}/°C	tem_{out}/°C	$Time_{in}$/min
1.1	350	1150	50
1.2	750	1150	30
2.1	460	510	160
2.2	460	510	110
3.1	40	460	320
3.2	40	460	270
4.1	420	440	700
4.2	420	440	490
4.3	420	440	490
5.1	1050	1050	120
5.2	1050	1050	60
6.1	950	950	140
6.2	950	950	70
7.1	850	1020	130
7.2	750	1150	40
8.1	420	1100	150
8.2	650	1150	50

Batch 1: 8 workpieces, a total of 17 crafts (Demands vary widely)
Batch 2: 10 workpieces, a total of 21 crafts (Demands vary moderately)
Batch 3: 13 workpieces, a total of 26 crafts (Demands vary little)
Batch 4: 31 workpieces, a total of 64 crafts (Demands vary moderately)

In order to compare the optimization results, the simulated annealing algorithm is used to optimize the same batch of workpieces. The simulated annealing algorithm is a random optimization algorithm, and its optimization effect is good, but it may fall into a locally optimal solution. According to the optimization method proposed in this work, the scheduling optimization results are compared with the simulated annealing algorithm optimization results, as shown in Table 5. The specific final optimization results of batch 1 are shown in Table 6. Batch 4 workpiece time and power consumption change with iteration, as shown in Figure 4:

Table 5. Scheduling optimization results of each batch.

Batch	Scheduling Method	Total Time $Time_{all}$/min	Total Power Consumption W_{count}/GJ
1	This work	1762.67	9.36
	Simulated Annealing	1941.53	10.20
2	This work	2335.47	23.16
	Simulated Annealing	2508.40	28.08
3	This work	2444.33	13.20
	Simulated Annealing	2496.33	14.55
4	This work	6606.33	44.52
	Simulated Annealing	7302.86	52.77

Table 6. Batch 1 final optimization result.

Process Number	Heating Furnace	Heating Sequence
1.1	1	2
1.2	1	5
2.1	2	2
2.2	1	3
3.1	2	1
3.2	2	3
4.1	1	1
4.2	2	4
4.3	2	5
5.1	1	6
5.2	1	8
6.1	1	7
6.2	1	9
7.1	1	10
7.2	1	11
8.1	1	4
8.2	1	12

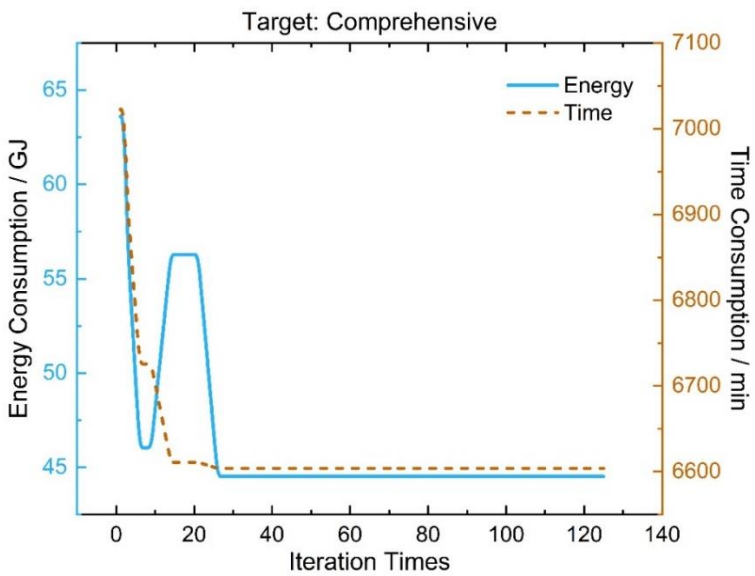

Figure 4. The change in time and energy consumption of batch 4 in the iterative process.

According to the results in Table 5, the final results obtained using the scheduling method in this work are better than those obtained by the simulated annealing scheme. Compared with the simulated annealing algorithm, this work not only saves more time but also saves more power consumption. In this work, the genetic algorithm is used to optimize the production scheduling scheme and reduce the energy consumption and waiting time of the heating furnace when the workpiece is not placed to achieve the optimization purpose. This work selects four batches of orders to save an average of 6.93% in time and 12.99% in energy. It can be seen that the energy-saving scheduling method proposed in this work can significantly reduce the total energy consumption while significantly shortening the total time of production orders.

4.2. Change Optimization Goals

The fitness calculation method is changed to:

$$fitness = e^{W_{exp} - W_{count}} + \frac{Time_{exp}}{Time_{count}} \tag{21}$$

This fitness calculation method amplifies the influence of the time parameter on the fitness and reduces the influence of the power consumption parameter. Taking batch 4 workpieces as an example, the iterative effect using the modified fitness calculation method is shown in Figure 5. The final consumption time is 6479.80 min, and the energy consumption is 48.95 GJ. Under this optimization objective, the average time saving is 10.35%, and the average energy saving is 10.63%.

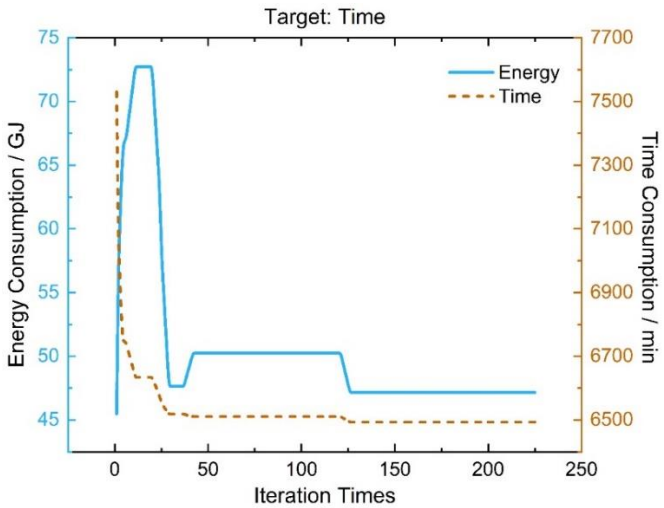

Figure 5. The change in time and energy consumption when thinking more about the time parameter in the iterative process.

The fitness calculation method is changed to:

$$fitness = e^{Time_{exp} - Time_{count}} + \frac{W_{exp}}{W_{count}} \tag{22}$$

This fitness calculation method amplifies the influence of power consumption parameters on fitness and reduces the influence of time. Using this method to optimize the scheduling of batch 4 workpieces, the final consumption time is 7063.54 min, and the energy consumption is 42.12 GJ. Under this optimization objective, the average time saving is 3.89%, and the average energy saving is 16.53%.

Comparing Figure 5 with Figure 4, it can be seen that, in comprehensive consideration, energy consumption should not be significantly sacrificed to reduce time. However, when time is given priority, it is acceptable to sacrifice energy consumption in many cases. Thus, by changing the fitness function, the optimization goal of the algorithm can be obviously changed.

It can be seen from the results that, by changing the calculation method of fitness, the emphasis of the final iterative solution can be changed. By adjusting the proportion of power consumption and time in the fitness calculation equation, the solution obtained from the last iteration can be adjusted to be more inclined to optimize energy or time. It can be seen that the optimization method proposed in this work can be applied to order scheduling schemes with different requirements.

4.3. Practical Factory Data Analysis

To illustrate the reliability of the results in this work, a two-day production process of this factory was selected for analysis. In these two days, the factory produced a batch of batch 1 orders. Production was carried out according to the order in Table 5. The factory used forklifts to transport workpieces. The final consumption time of batch 1 orders was 1805.55 min, and the energy consumption was 9.51 GJ. Compared with the simulation results, the errors in actual time and energy consumption are 2.4% and 1.6%. At the same time, the actual results are still better than those of the simulated annealing. The difference

between the actual production process and the simulation process was analyzed. Statistics on the problems in the actual production process were produced. Statistics of unexpected events in actual production are shown in Table 7.

Table 7. Problems encountered in practical factory production.

Problems	The Time Required to Solve the Problem/min	Impact on Total Time/min	Impact on Total Energy/MJ
Changing the workpieces in the heating furnace	8.23	8.23	15.16
Transferring workpieces	24.18	14.76	61.24
Machine inspection	4	7.32	13.20
Mechanical arm grabbing error	1.57	1.10	3.94
Heating delay	11.47	11.47	54.19

The table shows four problems encountered in actual production. Due to the large workpiece volume, replacing the workpiece in the heating furnace takes a lot of time, and for the workpiece with multiple production processes, its diameter will gradually become larger, which makes it more difficult to replace the workpiece. However, the time change caused by the larger diameter cannot be calculated. There are only two forklifts in the factory, and so each forklift must transport different workpieces repeatedly. Because there are many process steps in each workpiece, forklift trucks often need to transport the same workpiece many times. Because of the large diameter of the ring forgings, the space required to store the ring forgings is ample. This increases the distance traveled by forklifts and prolongs the total time of production orders. However, the placement position of the workpiece is usually random, and it is difficult to calculate its optimal position. Because the power of the heating furnace usually fluctuates within an arbitrary range, the actual temperature rise of the furnace is slower than the ideal situation, and the actual heating power is generally unpredictable. Thus, the problems shown in Table 7 are all force majeure problems. The above problems are the reasons for the error between simulation results and experimental results, and all problems are unavoidable. However, the error between actual production and the simulation results is within an acceptable range, and so the simulation results have high reliability.

For the problems listed in Table 7, it has little impact on the whole order when there are fewer workpieces. However, if there are many workpieces, forklift trucks will spend a lot of time transferring workpieces. Therefore, with the increase in workpieces, it is necessary to consider the path of forklifts. Optimizing forklift paths and combining them with a fitness function is an excellent direction for future research.

5. Conclusions

Focusing on the optimization problem of production scheduling of ring forgings, this work aims to reduce the time and energy consumed in the forging process and uses a genetic algorithm to optimize production scheduling. The conclusions can be drawn as follows:

(1) The production scheduling of ring forgings was optimized. According to the characteristics of ring forgings, a scheduling model was established. The temperature requirement of the ring forging was changed into the temperature of the heating furnace. According to the multi-process characteristics of ring forgings, the legitimacy modification function was designed to ensure that the genetic algorithm could optimize the sequence of forgings. At the same time, the simulation algorithm was designed to simulate the production process, and the temperature change of the heating furnace was obtained.

(2) The actual production process in the factory was selected for analysis. The problems encountered in actual production were recorded, and the impact of each problem on the overall time and energy consumption was counted. Compared with the

practical factory data, the errors in simulation time and energy consumption were 2.4% and 1.6%. The simulation results were close to the actual results, revealing that the simulation results had high reliability.

(3) In this work, four batches of sample data were optimized by way of example. When the optimization objective was designed to consider energy consumption and time consumption comprehensively, the average time saving was 6.93%, and the average energy saving was 12.99%. When the optimization objective was designed to prioritize energy consumption, the average time saving was 3.89%, and the average energy saving was 16.53%. When the optimization objective was designed to prioritize time consumption, the average time saving was 10.35%, and the average energy saving was 10.63%. Compared with traditional algorithms, the algorithm in this work had a better optimization effect.

The research in this work has important guiding significance for saving time and energy consumption of large-volume ring forging orders. It had a good effect on the actual factory simulation. The follow-up research of this work will focus on dealing with various interferences in the actual process and solving the handling of unexpected situations in the production process to ensure that the whole algorithm can be better applied in actual production.

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