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Intelligent Blanking of Silicon Steel Coil in a Transformer Core Oriented to Green Manufacturing

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Abstract: For transformer enterprises, energy consumption and environmental pollution mainly occur in the manufacturing process. The conventional manufacturing mode does not conform to the current green manufacturing mode. The green manufacturing mode requires enterprises to improve the transformer production technology, the utilization rate of materials and equipment, and the production efficiency and to achieve clean production through energy conservation and consumption reduction. The main objective of this research is to schedule the blanking of multiple transformer cores together rather than the conventional calculation conducted one by one. An optimization model of the silicon steel coil blanking is established, an evaluation method for blanking schemes is proposed, algorithms to solve the optimization model are analyzed in detail, and the solving processes and results are compared through a case study. Compared with the current manual calculation, this paper is of practical significance for transformer manufacturers to improve the production efficiency, reduce material waste, meet the personalized market demand characterized by multiple varieties and small batches, and achieve the green manufacturing of transformers.

Keywords: green manufacturing; transformer core; intelligent scheduling

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1. Introduction

Carbon emissions in the power industry account for a high proportion within the energy industry, and distribution loss is an important source of carbon emissions [1]. Decarbonization in the power industry is the top priority, and green transformers will become a key piece of electrical equipment for energy efficiency and emissions reduction in the process of achieving the goal of "double carbon". The main technical characteristics of green transformers are energy savings, material savings, and environmental protection. The green manufacturing of transformers requires that transformers and their components meet the requirements of low energy consumption, a high material utilization rate, and low waste in production [2]. Therefore, how to realize the green development of the transformer manufacturing industry has become an urgent issue facing the whole industry.

As an important part of a transformer, the conventional production process of a transformer core is shown in Figure 1. The slitting machine cuts the silicon steel coil into semi products of a certain width along the longitudinal direction; the cross-cutting machine cuts the semi products into pieces of the required shape; and, finally, the pieces of sheets are stacked into transformer cores in accordance with the prescribed sequence. Blanking refers to cutting the silicon steel coil into semi products of a certain width along the longitudinal direction; it is the first step in the production process of a transformer core. Scheduling refers to determining the width of the semi products according to the demand of customers' orders; it is the key to blanking. In the current transformer core production process, scheduling is usually calculated manually one by one; thus, the workload is heavy, the efficiency is low, and the utilization rate of the silicon steel coils is not maximized. Increasingly, the personalized transformer core market demand, characterized by multiple varieties and small batches, also poses new challenges for manual scheduling. Therefore, blanking scheduling must be more intelligent and leaner to reduce production costs, improve production efficiency, and quickly respond to the changing market demand.

Figure 1. Production process of a transformer core.

Prochazka [3] focused on the design and realization of a magnetic circuit of a transformer operating at a nominal voltage of 10 kV and in a frequency range from 200 Hz up to 10 kHz. Zhao [4] presented an automatic on-load voltage-regulating distributing transformer that employed a noncontact solid-state relay as a tap-changer and introduced its structure, the basic principal, and the design methods of each key link. Yang [5] proposed a simulation test system for a noncontact D-dot transformer for voltage measurement, which consisted of a D-dot transformer, a signal processing circuit, and a ground PC port. Chraygane [6] presented a new approach for the study of the behavior of a new three-phase high-voltage power supply for magnetrons in a nonlinear regime, which is used for microwave generators in industrial applications. Kruzhaev [7] constructed a transformer model considering the saturation of the steel of the core, which differed from standard models. Zheng [8] presented an improved conceptual design option of an equipotential shielding capacitor voltage transformer to improve the shielding effect without an increase in the shielding capacitance. Doan [9] analyzed the winding voltages, inrush currents, and flux density inside the core of each transformer. Xiang [10] presented a circuit evolution of the high step-ratio transformer-coupled RMMC into its low step-ratio transformer-less RMMC counterpart. Kharezy [11] designed a compact solution for an energy collections system that allowed for a minimum of total transformer weight. It is obvious that all these studies on transformers made great contributions to structure, principle, and design methods to improve their performance. However, the literature on the use of advanced manufacturing technologies to improve the production process, reduce production costs, and improve production efficiency of transformers is limited.

In this paper, the scheduling of silicon steel coil blanking was regarded as a combinatorial optimization problem: the mathematical model was established, the evaluation method of the scheduling was put forward, the solving algorithms of the model were studied, and the intelligent scheduling of the silicon steel coil blanking studied in this paper was verified through cases.

The rest of this article is organized as follows: Section 2 establishes the optimization model of the silicon steel coil blanking; Section 3 analyzes the algorithms to solve the optimization model in detail; Section 4 compares the solving processes and results of the algorithms through a case study to determine the optimal one; and Section 5 lists some conclusions and contributions of this article.

2. Establishment of Model

The goal was to determine the blanking sequence of the semi products according to the order demand and to minimize the surplus material and maximize the utilization rate of the silicon steel coil. Assume that a total of n kinds of semi products are needed according to the order; bi is the width of the semi products; di is the quantity of the semi products with the same width; and B is the width of the silicon steel coil. Here, i represents the type of the semi products, and its value is $i = 1, 2, \ldots, n$. Assume that the order demand is divided into m groups; a_{ij} represents the quantity of the type i blanking from a single silicon steel coil in group j. Here, j represents the number of a group, and its value is $j = 1, 2, \ldots, m$. The coefficient matrix can be obtained as

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \tag{1}$$

Suppose y_j represents the width of the residual material from a single silicon steel coil in the group j, then

$$y_j = B - \left(a_{1j}b_1 + a_{2j}b_2 + \cdots + a_{nj}b_n\right) \tag{2}$$

where x_j represents the quantity of silicon steel coils needed in group j, and the total quantity of silicon steel coils is

$$X = \begin{pmatrix} x_1 & x_2 & \cdots & x_m \end{pmatrix}^T \tag{3}$$

Therefore, the sum width of the residual material is

$$Y = y_1x_1 + y_2x_2 + \cdots + y_mx_m = \sum_{j=1}^{m} y_jx_j \tag{4}$$

The goal was to minimize the residual material. Moreover, market experience shows that residual material with a width less than 60 mm can neither be used for the next blanking nor be directly cross-cut into silicon steel sheets and, thus, become waste. Therefore, it is necessary to guarantee that the width of the residual material is not less than 60 mm. Then, the optimization model of the silicon steel coil blanking is obtained as

$$\text{objective function}: \ \min \sum_{j=1}^{m} y_jx_j \tag{5}$$

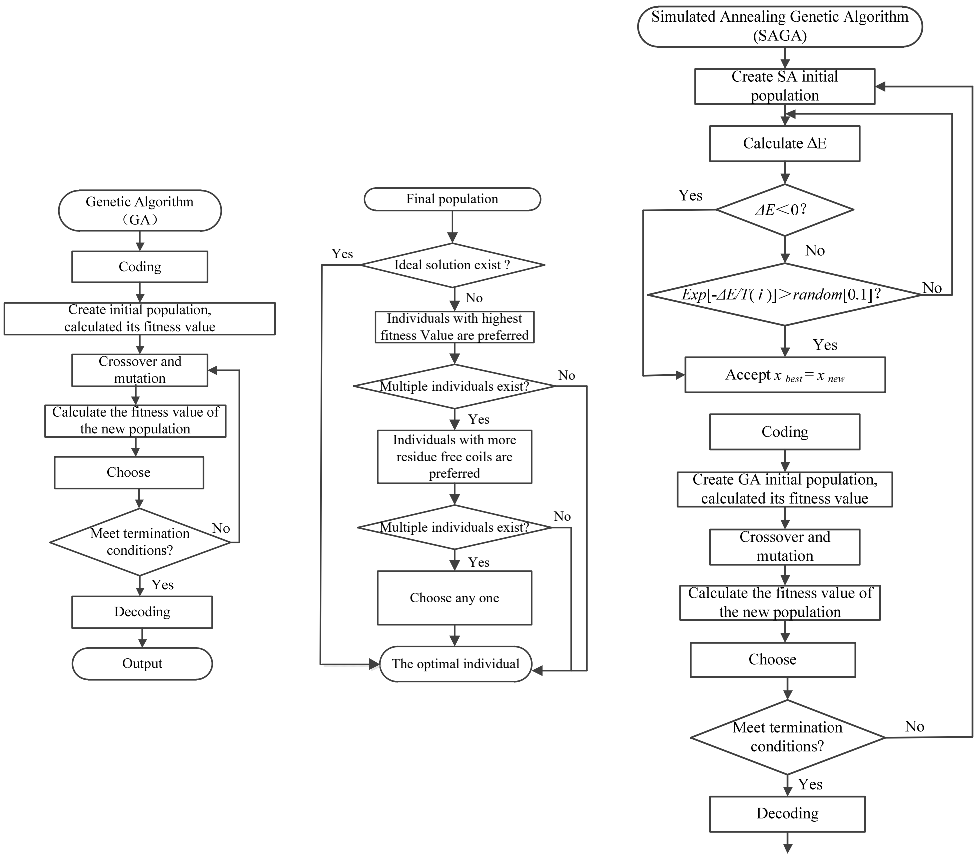
$$\text{constraints}: \begin{cases} \sum_{j=1}^{m} a_{ij}x_j = d_i \quad (i = 1, 2, \ldots, n) \\ x_j \geq 0 \quad (j = 1, 2, \ldots, m) \\ y_j \geq 60 \end{cases} \tag{6}$$

3. Solving Algorithms of the Model

If the production volume of the transformer core in the order is large, there will be several feasible plans for the silicon steel coil blanking, and a stochastic algorithm is usually used to solve the optimization model. The genetic algorithm and the simulated annealing algorithm are the two typical stochastic algorithms. The genetic algorithm has good efficiency, but it may appear to have local convergence and premature convergence [12–14]. The simulated annealing algorithm has good robustness and strong local searching ability, but its shortcoming is low efficiency [15–18]. Considering the advantages and disadvantages of the simulated annealing algorithm and genetic algorithm, a hybrid simulated annealing genetic algorithm was adopted in this paper, which introduced a genetic operation after a simulated annealing operation. In this way, it can take full advantage of the strong local search ability of the simulated annealing algorithm to avoid local convergence and premature convergence. Meanwhile, a genetic operation can also improve the search efficiency of the simulated annealing algorithm.

3.1. Solving Process of the Genetic Algorithm

The genetic algorithm is an intelligent optimization algorithm that searches for the optimal solution by simulating the process of biological evolution [19–21]. It is often used to find the optimal solution from a series of combinations. In Figure 2, GA stands for genetic algorithm, SA stands for simulated annealing algorithm, and SAGA represents simulated annealing genetic algorithm.



(**a**) (**b**) (**c**)

Figure 2. Solving process. (**a**) GA process. (**b**) optimal solution selection process. (**c**) SAGA process.

As shown in Figure 2a, the first step in the GA process is coding, and decimal coding was adopted in this paper. Assume that a total of n kinds of semi products are needed according to the order; b_i is the width of the semi products; d_i is the quantity of the semi products with the same width; N is the total quantity of all the semi products; and B is the width of the silicon steel coil. Here, $N = \sum_{i=1}^{n} d_i$, i represents the type of the semi products, and its value is $i = 1, 2, \ldots, n$. Each semi product to be produced is numbered as $1, 2, \ldots, p_i, \ldots, N$; p_i is a specific and nonrepeated number, and its value range is $[1, N]$. In this way, each semi product is mapped with a digital code. A sequence of the digital code is called an individual, which represents the width sequence of a scheduling scheme, namely, the blanking sequence.

The second step is to create the initial population. After coding, all of the digital codes are randomly arranged to generate an ordered sequence, that is, the initial population. Moreover, the fitness value of everyone in the initial population needs to be calculated. The higher the fitness value, the better the individual, and its maximum value is 1. Suppose that the digital code sequence of an individual P is known, and the width of the semi products corresponding to each digital code is accumulated according to the sequence. When the width sum is equal to the width of a silicon steel coil, the number of silicon steel coils increases by 1 to obtain the number of silicon steel coils required by this individual. For the blanking scheduling problem studied in this paper, the reciprocal of the silicon steel coil number was usually taken as the fitness value. However, market experience shows that the residual material with a width less than 60 mm can neither be used for the next blanking nor be directly cross-cut into silicon steel sheets and, thus, become waste. Therefore, the optimal scheduling scheme should not only ensure less residual material, but residual material is also concentrated on the last silicon steel coil as much as possible. Accordingly, the fitness value is defined as

$$f(P) = \sum_{i=1}^{N} b_i \cdot d_i / [B \cdot M - Y_m] \tag{7}$$

where M is the number of silicon steel coils required by the individual P, and Y_m is the width of the residual material of the last silicon steel coil.

The third step is to cross and mutate the parent population. Suppose that there are S individuals in the parent population, and the individuals in the parent population cross each other randomly to generate S offspring individuals. Single-point crossover and double-point crossover are the two common crossover methods. Suppose that two individuals $U = \{u_1,u_2,u_3, \ldots u_N\}$ and $V = \{v_1,v_2,v_3, \ldots v_N\}$ are the two individuals in the parent population. Single-point crossover is to randomly select a point p_1, and then the elements before the point p_1 in individual U is copied to the same position in the child individual U_{new}; the rest of the elements in U are copied to the child individual U_{new} in accordance with the sequence as they appear in V. The child individual V_{new} can be obtained in the same way as shown in Figure 3a. The double-point crossover randomly selects two cross points, p_1 and p_2, and then the elements between the cross points, p_1 and p_2, in individual U are copied to the same position in the child individual U_{new}; the rest of the elements in U are copied to the child individual U_{new} in accordance with the sequence as they appear in V. The child individual V_{new} can be obtained in the same way as shown in Figure 3b. When the population is small or the cross point is located at the end of the parent individuals, it is easy for the single-point crossover to happen so that the child individual is identical to the parent individual, such as Figure 3a. When the two cross points are adjacent, the double-point crossover will have the same problem, but it can be avoided by some regulations. Therefore, the double-point crossover method was adopted to implement the crossover operation, which can avoid the local optimum.

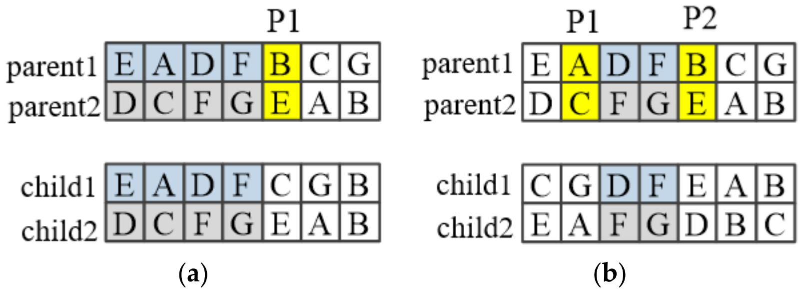


Figure 3. Crossover methods. (**a**) single-point crossover. (**b**) double-point crossover.

At the same time, a mutation operation is also needed. Two points of the child individuals are randomly selected as mutation positions, and the codes at the mutation positions are exchanged. The purpose of the mutation operation is to avoid the local optimum.

After the above steps, it is necessary to choose better individuals from the parent population and the child population. The parent individuals and child individuals are ranked according to their fitness values, and S individuals with larger fitness values are chosen as the parent population of the next cycle. The termination conditions of the cycle are that the cycle index reaches the maximum or the population fitness values remain at the maximum. The cycle ends once one of them is satisfied.

Finally, the final population needs to be decoded. However, not all individuals in the final population are optimal, so it is necessary to select the optimal individuals from the final population. As shown in Figure 2b, if there are ideal solutions in the final population, that is, all the residual materials are concentrated on the last silicon steel coil, then one ideal solution is selected as the optimal individual. If there is no ideal solution in the final population, the individual with the higher fitness value is selected as the optimum. If there are multiple individuals with the same fitness value, the individual with the least number of residual silicon steel coils is selected as the optimum. If both are identical, anyone of them is chosen as the optimum.

3.2. Solving Process of the Simulated Annealing Genetic Algorithm

The simulated annealing genetic algorithm overcomes each other's shortcomings and improves the overall performance through combining the simulated annealing algorithm with the genetic algorithm. It carries out simulated annealing operations for each individual of the initial population and then generates a new generation of the population through crossover and mutation. The cycle is repeated until the termination conditions are met, as shown in Figure 2c.

The first step is to randomly arrange all the semi products needed by the order to generate a width sequence, that is, the initial population.

The second step is to perform the single-point crossover for each individual of the initial population, thus generating a new individual. Suppose x_{ini} represents an initial individual; x_{new} is the new individual, and $\Delta f = f(x_{new}) - f(x_{ini})$ is the increment of fitness value. When $\Delta f < 0$, x_{new} is accepted as a child individual. When $\Delta f \geq 0$, judge whether $\exp[-\Delta f/T] >$ random [0.1]; if so, x_{new} is accepted as a child individual, otherwise return to the initial individual to generate a new individual. Here, $T = r \times T$; r is generally 0.8–0.99.

The following operations are the same as the genetic algorithm.

4. Case Study

The width of the silicon steel coil used in a transformer manufacturer is 1000 mm. Suppose that an order demand is three transformer cores; the widths of the semi products for the three transformer cores are, respectively, {50, 70, 100, 110, 120, 130, 160}, {50, 90, 90, 100, 120, 130, 150}, and {70, 90, 100, 110, 140, 165}; the unit here is mm. If the blanking is carried out one by one, according to the currently used method, the blanking scheme is shown in Table 1, and the fitness value is 0.89.

Table 1. Current blanking scheme.

Silicon Steel Coil	Blanking Width Sequence	Residual Material Width
1	{50, 70, 100, 110, 120, 130, 160, 50, 90}	120
2	{90, 100, 120, 130, 150, 70, 90, 100}	150
3	{110, 140, 165}	585

The optimization model of the silicon steel coil blanking was established, the algorithms studied in this paper were adopted to solve the model, and the solving processes and results of these algorithms were analyzed to obtain the optimal blanking scheme.

4.1. Comparison of the Parameters

Firstly, the genetic algorithm studied above was used to analyze the influence of the crossover rate, P_{cross}, and mutation rate, P_{mut}, on the solution process and results. Let $P_{cross} = 0.7$, and the value of P_{mut} is 0.05, 0.1, 0.15, and 0.2. The relationships between the fitness values and iteration steps are directly described as per the curves in Figure 4. It can be seen from Figure 4 that the search efficiency of the algorithm presented a growth trend with the increase in the mutation rate, P_{mut}, and the iteration steps needed to reach a stable fitness value decrease. However, when P_{mut} reached 0.15, increasing its value had little effect on the algorithm's performance.

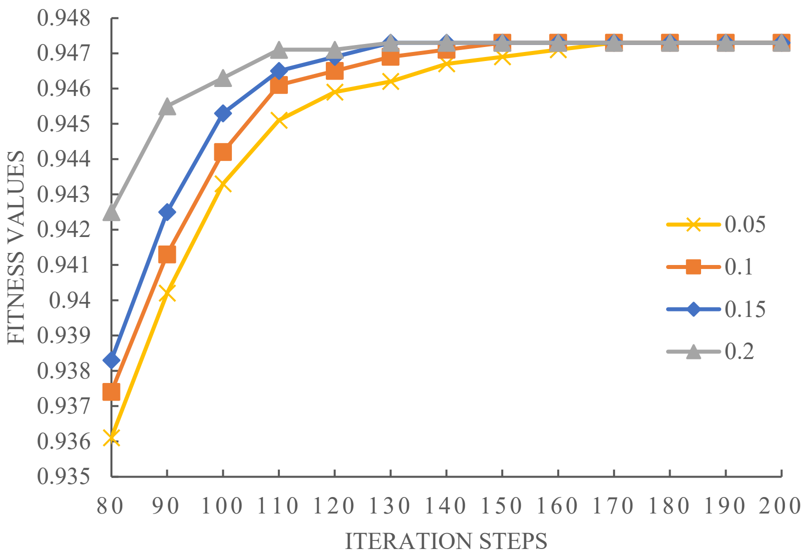


Figure 4. Relationship between the fitness value and iteration steps when P_{mut} varied.

Let P_{mut} = 0.15, and the value of P_{cross} is 0.6, 0.7, 0.8, and 0.9. The relationships between the fitness value and iteration steps are directly described as per the curves in Figure 5. It is demonstrated in Figure 5 that the iteration steps needed to reach a stable fitness value decrease with the increase in the crossover rate, P_{cross}. When the iteration steps reached 130, the fitness values were basically close, although P_{cross} varied. Considering that the increase in P_{cross} will lead to more running time, the appropriate value of P_{cross} should be 0.7.

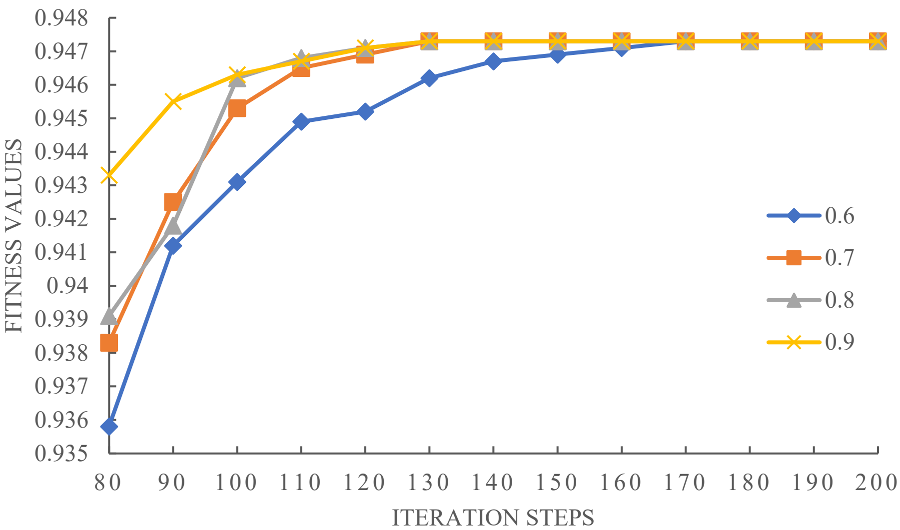


Figure 5. Relationship between the fitness value and iteration steps when P_{cross} varied.

4.2. Comparison of the Search Efficiency

In order to verify the performance of the simulated annealing genetic algorithm (SAGA), it was compared with the genetic algorithm (GA). Let P_{cross} = 0.7 and P_{mut} = 0.15. The GA and SAGA were adopted to solve the optimization model, and the relationships between the fitness values and iteration steps are described as per the curves in Figure 6. It can be seen that the GA fell into local convergence when the iteration steps reached

130. The SA avoided local convergence but required 160 iteration steps to reach a stable fitness value. The SAGA not only avoided local convergence but also improved the search efficiency to quickly solve the optimal blanking scheme.

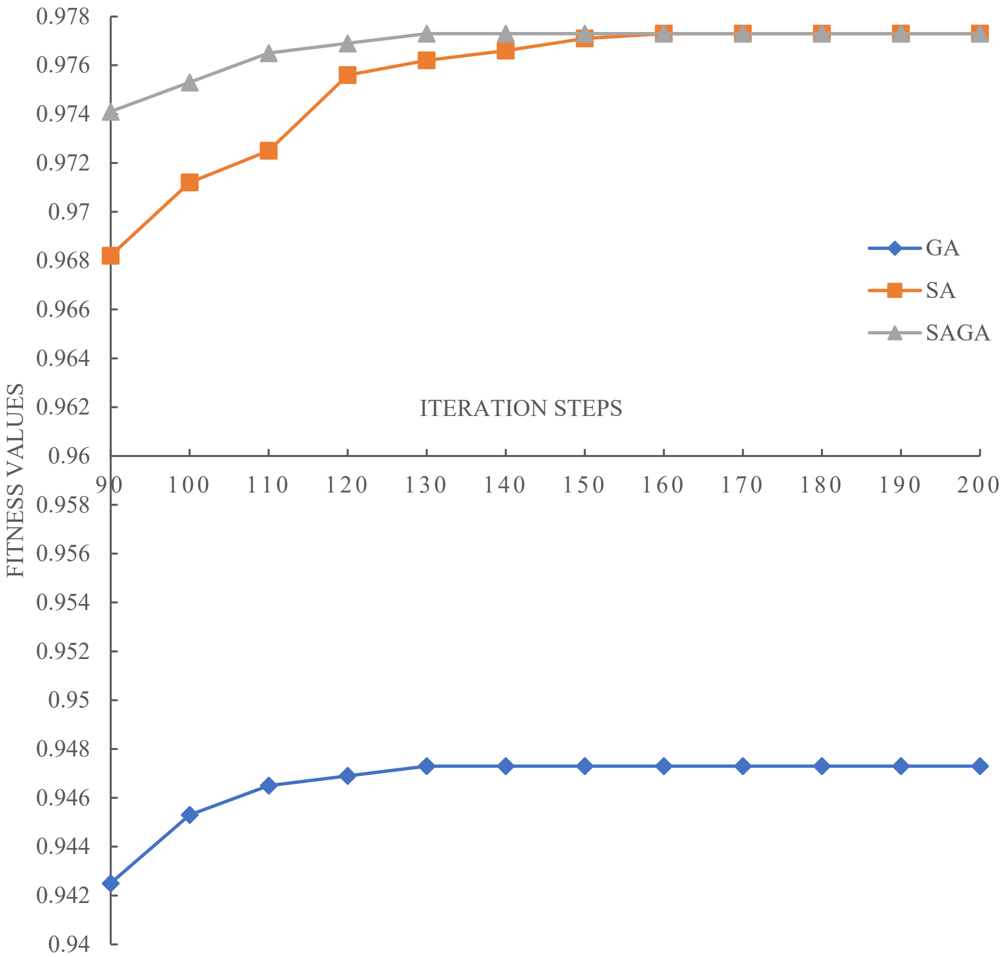


Figure 6. Comparison of the algorithms' performance.

Some individuals in the final population solved by the above simulated annealing genetic algorithm were decoded to obtain the blanking scheme, as shown in Figure 7. The fitness value of all of these schemes was 0.9773, which is better than the current blanking scheme shown in Table 1. Since they had the same number of 0 residual silicon steel coils, anyone of the blanking schemes shown in Figure 7 is appropriate.

silicon steel coil 1									residual	silicon steel coil 2									residual	silicon steel coil 3			residual
110	130	160	150	100	70	110	50	120	**0**	140	90	100	90	100	130	120	165		**65**	70	90	50	790
110	70	100	90	150	140	120	130	90	**0**	90	70	130	120	165	50	50	160	100	**65**	110	100		790
50	90	140	130	90	100	70	100	165	**65**	120	150	110	160	70	110	50	100	130	**0**	90	120		790
140	90	50	110	130	160	150	100	70	**0**	110	120	100	90	100	130	120	165		**65**	70	90	50	790
110	70	100	90	150	140	50	130	160	**0**	110	120	100	90	100	130	120	165		**65**	70	90	50	790

Figure 7. Optimized blanking schemes.

5. Conclusions

Aimed at the problems of a heavy workload, low efficiency, and low utilization rate of the silicon steel coil in the production of a transformer core, the intelligent scheduling of silicon steel coil blanking was studied in this paper. It was proved that the optimization model of the silicon steel coil blanking established in this paper together with the simulated annealing genetic algorithm obtained the optimal blanking scheme quickly and effectively. Compared with the current blanking scheme, it significantly improved the utilization rate of the silicon steel coil. The simulated annealing genetic algorithm not only avoided local convergence but also enhanced the search efficiency so as to quickly solve the optimal blanking schemes. The appropriate algorithm parameters should be selected to balance the relationship between the algorithm's performance and the fitness value.

The main contribution of this paper is that it proposes an intelligent scheduling of silicon steel coil blanking for transformer core manufacturing. It schedules the blanking of multiple transformer cores together rather than the conventional calculation one by one. The optimization model of the silicon steel coil blanking was established, an evaluation method for the blanking schemes was proposed, the algorithms to solve the optimization model were compared in detail, and the optimal algorithm was found. Compared with the current manual calculation, this paper is of practical significance for transformer manufacturers to improve the production efficiency, reduce material waste, meet the personalized market demand characterized by multiplr varieties and small batches, and achieve the green manufacturing of transformers.

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