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Parameter Optimization Design for Automatic Cotton Blending Based on Improved Adaptive Genetic Algorithm

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Abstract. *According to the characteristics of computer distribution in multi constraint conditions, in order to further improve the versatility and adaptability of computer automatic cotton, this paper put forward a kind of improved adaptive genetic algorithm optimization method. Through establishment of the mathematical model of cotton blending, we turn it into the optimization problems with multiple constraints. On the basis of analysis of the standard genetic algorithm shortcomings in the process parameters optimization of mechanized cotton. In the optimization of process, the variation of the variation and the probability of crossover is changed automatically, which can ensure the convergence of the algorithm and maintain the diversity of the population. Experimental results show that by adopting improved adaptive genetic algorithm strategy in the process of cotton blending, optimizing speed, precision, the ability of local and global optimization and other indicators have been improved, reducing the cotton distribution costs of enterprises, thus has a certain guiding significance and practical application value.*
Keywords: Cotton blending, Improved adaptive genetic algorithm, Parameter identification

1. **Introduction.** Cotton assorting refers that cotton spinning enterprises select a part of batch cotton for processing and mixing of inventory raw cotton in order to meet the requirements of some spinning and yarn quality, and it is a process for determining the best match cotton mixing ratio. In the past, cotton blending was completed by the operator manually with low efficiency. Computer automatic cotton assorting can effectively overcome limitations thereof relative to manual cotton assorting with application of automatic control and computer technology in cotton assorting process. Genetic algorithm is a worldwide probability search algorithm. Its principle is formed on the basis of chromosomal mutation, natural selection and other biological evolution mechanism. Some excellent performances and effects are also displayed in the solution of cotton assorting combinatorial optimization [1]. There continue to be some defects in conventional standard genetic algorithm, such as premature convergence, slow convergence speed and other deficiencies. In the paper, cotton assorting process is analyzed. Control strategy of standard genetic algorithm needs to be improved on the basis of analyzing disadvantages of standard genetic algorithm. Automatic optimization performance of cotton assorting parameter is improved in cotton assorting process optimization [2].

2. **Cotton assorting mathematical model.** Cotton assorting plan must meet the yarn count requirements regulated by clients. These requirements are the basic constraint conditions of automatic cotton assorting.

2.1. **Objective function.** Economic mathematics model should be established in order to optimize cotton assorting engineering. Economic benefits of cotton assorting process plan are generally regarded as objectives [3, 4]. The minimum value of cotton assorting process cost is generally regarded as objective function:

$$\min Z(x) = \sum_{i=1}^{n} S_i * X_i \tag{1}$$

In the formula, S_i represents unit price of the ith raw cotton; X_i represents the proportion of the ith raw cotton in total cotton in the automatic cotton assorting process; n represents batch cotton variety quantity of cotton assorting process. Objective function aims at tossing the optimal batch cotton ratio on the basis of meeting various constraint conditions. Therefore cotton assorting cost $Z(x)$ can be minimized, and the cost can be lowered [4].

2.2. **Cotton assorting constraints.** There are many factors affecting cotton assorting, and they must conform to conditions with decisive role on cotton assorting, mainly including batch cotton proportion and yarn quality constraints [5].

(1) Lower constraints of quality indicators

$$\sum_{i=1}^{n} L_i * X_i > Y(1) \tag{2}$$

In the formula: L_i refers to yarn quality of the ith raw cotton, such as single yarn strength, and other indexes. $Y(1)$ refers to quality indicator target value of to-be-spun yarn.

(2) Upper constraints of quality indicators

$$\sum_{i=1}^{n} H_i * X_i < Y(2) \tag{3}$$

In the formula: H_i refers to the number of single yarn quality defects test spinning value of the ith raw cotton. $Y(2)$ is the target value of the defect number of the spinning yarn

(3) Raw material component constraints

$$\sum_{i=1}^{n} W_i * X_i < Y(3) \tag{4}$$

In the formula, W_i refers to a related factor. If ith raw material is selected as the main component, $W_i = 1$ can be selected, otherwise $W_i = 0$ can be selected. $Y(3)$ is value for determining raw cotton main component.

(4) Batch cotton proportional constraints

$$\sum_{i=1}^{n} X_i = 1 (a_i \leq X_i \leq b_i) \tag{5}$$

In the formula: the proportion sum of all cottons in the cotton assorting plan is 1, bi and a_i respectively refer to the upper limit and lower limit of proportion of the ith batch cotton.

3. **Genetic algorithm and improvement strategy.** Standard genetic algorithm (hereinafter referred to as SGA) is a kind of random search and optimization algorithms for imitating evolution of biological group. Basic idea of SGA comes from Darwin's evolution theory and Mendel's genetics that knowledge about searching space can be automatically obtained and accumulated in the searching process. SGA robustness is stronger, knowledge of professional field, required in parameter optimization solution, is less, and it is widely applied in engineering optimization [6].

SGA has some deficiencies in practical applications:

(1) Premature convergence

Since genetic algorithm simply adopts individual fitness value to determine quality of solution, when the fitness value of some individual is larger, the individual gene can be rapidly diffused in the population, thereby the population can lose diversity too early. The solution fitness is not improved further, and it is trapped in local optimal solution, therefore global optimal solution cannot be searched [7].

(2) Local searching ability

Genetic algorithm has excellent performance in the aspect of global search. The global optimal solution cannot be still converged [8].

3.1. **Conventional adaptive genetic algorithm.** Some scholars improve standard genetic algorithm and propose adaptive genetic algorithm (hereinafter referred to as AGA). The algorithm has the following main idea that the defect of fixed and consistent mutation and crossover probability in the genetic algorithm is changed, and therefore mutation probability and crossover probability can be changed with fitness change in algorithm recognition:

Crossover probability

$$\begin{cases} P_c = P_{c1} - \dfrac{(P_{c1} - P_{c2})(F - F_{avg})}{F_{\max} - F_{avg}}, & F \geq F_{avg} \\ P_c = P_{c1}, & F < F_{avg} \end{cases} \tag{6}$$

Mutation probability

$$\begin{cases} P_m = P_{m1} - \dfrac{(P_{m1} - P_{m2})(F_1 - F_{avg})}{F_{\max} - F_{avg}}, & F_1 \geq F_{avg} \\ P_m = P_{m1}, & F_1 < F_{avg} \end{cases} \tag{7}$$

In the above formula: P_c is the crossover probability. P_m is the mutation probability. F is the maximum value of fitness in the current population group; $F_{\max}$ represents that the larger value of two individual fitness values in the population waiting and crossing process; F_{avg} refers to average fitness value of current population group; F_1 refers to fitness value of to-be-mutated individual [9].

The above formula shows that the iterations frequency is closer to the maximum set generation, the mutation probability rate is greater given, and the individual crossover probability rate is lower.

The method is beneficial for saving excellent individuals of subsequent population. The performance is improved compared with standard genetic algorithm. However, some individuals with better fitness can enter the static and constant state at the beginning of evolution, thereby the system can produce local convergence phenomenon [10].

3.2. **Improvement strategy of adaptive genetic algorithm.**

(1) Encoding methods

Floating-point encoding is adopted for issue related to more design variables. Floating-point encoding genes correspond to variables one by one, computation time of encoding and decoding can be reduced, thereby increasing search efficiency.

(2) Selection operator

Groups P with scale of n are sequenced according to individual fitness value descending order.

$$P = \{a_1, a_2, \ldots, a_n\} \tag{8}$$

Nonlinear unitary geometry is adopted for rehearsing functions, and selection probability of individual i is shown as follows:

$$\begin{cases} P(i) = q^l(1-q)^{r-1} \\ q^l = \dfrac{q}{1-(1-q)^n} \end{cases} \tag{9}$$

In the above formula: q^l is the possibility for selecting optimum individual, and r is individual serial number.

Then, roulette selection is depending on the probability [11].

(3) Crossover operator

Two-point arithmetic crossover operator is adopted, the follows are set:

$$w_1^t = (w_1^1, w_2^1, \ldots, w_k^1, \ldots, w_n^1), w_2^t = (w_1^2, w_2^2, \ldots, w_k^2, \ldots, w_n^2) \tag{10}$$

They are two chromosomes. Two-point arithmetic crossover is implemented from point i to point j. The following offspring can be produced:

$$w_1^{t+1} = (w_1^1, w_2^1, \ldots, w_{i-1}^1, w_i', \ldots, w_j', \ldots, w_n^1) \tag{11}$$

$$w_2^{t+1} = (w_1^2, w_2^2, \ldots, w_{i-1}^2, w_i'', \ldots, w_j'', \ldots, w_n^2) \tag{12}$$

Element w_k' in invector w_1^{t+1} and element w_k'' in invector $w_2^{t+1}\,(i \le k \le j)$ can be produced through the following combination:

$$\begin{cases} w_k' = \alpha w_k^1 + (1-\alpha) w_k^2 \\ w_k'' = \alpha w_k^2 + (1-\alpha) w_k^1 \end{cases} \tag{13}$$

Wherein $\alpha \in (0,1)$, w_k^1 is element of invector w_1^t, w_k^2 is element of invector w_2^t.

(4) Mutation operator

The following improved mutation operators are adopted in order to achieve rapid convergence of algorithm and prohibit premature phenomena of population.

Specific operation is shown as follows: individual chromosome is set as $w = (w_1, w_2, \ldots, w_k, \ldots, w_n)$, wherein element $w_k \in [L_k, U_k]$ is the selected mutation, and the element's mutation results are shown as follows:

$$w_k' = \begin{cases} w_k + |s(U_k - w_k)|, & r < 0.5 \\ w_k - |s(w_k - L_k)|, & r \ge 0.5 \end{cases} \tag{14}$$

In the formula, r is uniform random variable within the limits of 0 to 1, and s is a random number meeting Gauss distribution.

(5) Improvement of crossover and mutation probability

In the paper, an improved adaptive genetic algorithm (hereinafter referred to as IAGA) is proposed in order to improve the shortage of AGA algorithm. Dynamic adaptive adjustment is implemented on crossover and mutation probability. The adjustment formula is shown as follows:

Crossover probability

$$\begin{cases} P_c = P_{c1} - \alpha \times \dfrac{(P_{c1} - P_{c2})(F - F_{avg})}{F_{\max} - F_{avg}}, & F \geq F_{avg} \\ P_c = P_{c1}, & F < F_{avg} \end{cases} \tag{15}$$

Mutation probability

$$\begin{cases} P_m = P_{m1} - \alpha \times \dfrac{(P_{m1} - P_{m2})(F_1 - F_{avg})}{F_{\max} - F_{avg}}, & F_1 \geq F_{avg} \\ P_m = P_{m1}, & F_1 < F_{avg} \end{cases} \tag{16}$$

Wherein, the adjustment coefficient α value is shown as follows:

$$\alpha = \frac{2.2}{1.1 + e^{\frac{n}{N}}} \tag{17}$$

In the formula: n refers to the current iteration number; N refers to the maximum iteration number.

Adjustment idea of the above formula is shown as follows: greater crossover probability and mutation probability are always adopted for individuals smaller than average fitness, which is beneficial for eliminating worse individuals [12]. The crossover probability and mutation probability are always decreased with increase of fitness aiming at individuals larger than or equal to average fitness. In addition, crossover probability and mutation probability are smaller and smaller with the increase of evolution generation.

Appropriate crossover probability and mutation probability can be obtained for individuals with larger fitness at the early evolutionary period in the adjustment method. The algorithm has stronger global searching ability [13]. The algorithm's global searching ability is abated and local searching ability is enhanced with increase of evolutionary generation. Therefore, it is convenient to find global optimal solution. The control strategy can make the species individuals to achieve relatively appropriate crossover probability and mutation probability in all stage of parameter optimization, thereby making up individual differences of population, and increasing the global optimization searching ability of algorithm [14].

4. **Solution of cotton assorting process model by improved genetic algorithm.**

4.1. **Optimization of objective function.** In the paper, related data of a cotton spinning enterprise are collected as basis for establishing cotton assorting model [15]. One cotton spinning factory required to process cotton yarn in some variety. Finished cotton is processed and produced by blending eight raw cottons in different batches. Inventory cotton materials in different batches are selected. Main process parameters of the batch cottons are known and shown in the following table 1:

Table 1. Cotton Price and Performance Parameters

Parameter	Batch of raw cotton							
	0301	0412	0713	0703	0127	0807	1109	0801
Unit Price (Million yuan/ton)	1.92	1.85	1.68	1.80	1.69	1.72	1.73	1.51
Short fiber rate (%)	7.9	7.8	9.4	12.2	8.1	9.2	9.6	13.0
Strength (CN/Tex)	34.1	31.4	26.9	29.3	27.5	29.1	28.7	24.9
Cotton impurity (Grain)	34	42	56	48	58	46	51	73
Proportional up limit (%)	8.1	14.2	12.2	15.1	18.1	27.9	16.9	8.9

Strength, nep impurities, short-staple rate and other major cotton assorting technology indicators are generally considered in the automatic cotton assorting optimization process. After cotton assorting processing is completed, newly produced cotton yarn quality standards are shown as follows: cotton yarn short-staple rate is not greater than 9.5. The strength is not less than 28.8; N Abstract nep impurity quantity is not more than 56, and it is expected that optimal cotton assorting cost can be obtained under the above constraints. Firstly, cotton assorting process mathematical model is established, and the automatic cotton assorting objective functions are shown as follows:

$$\min Z(x) = 1.92X_1 + 1.85X_2 + 1.68X_3 + 1.8X_4 + 1.69X_5 + 1.72X_6 + 1.73X_7 + 1.51X_8 \quad (18)$$

It is set that Xi is the blending proportion of the ith batch cotton (batch cotton is sequenced from left to right in table 1. The following cotton assorting constraints can be obtained:

$$\begin{cases} 7.9X_1 + 7.8X_2 + 9.4X_3 + 12.2X_4 + 8.1X_5 + 9.2X_6 + 9.6X_7 + 13X_8 \leq 9.5 \\ 34.1X_1 + 31.4X_2 + 26.9X_3 + 29.3X_4 + 27.5X_5 + 29.1X_6 + 28.7X_7 + 24.9X_8 \geq 28.8 \\ 34X_1 + 42X_2 + 56X_3 + 48X_4 + 58X_5 + 46X_6 + 51X_7 + 73X_8 \leq 56 \\ X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8 = 1 \\ X_1 \leq 0.081, X_2 \leq 0.142, X_3 \leq 0.122, \\ X_4 \leq 0.151, X_5 \leq 0.181, X_6 \leq 0.279, \\ X_7 \leq 0.169, X_8 \leq 0.089 \\ X_i \geq 0 \, (i = 1, 2, 3 \ldots 8) \end{cases} \quad (19)$$

4.2. **Flow of improved adaptive genetic algorithm.** Improved adaptive genetic algorithm is shown as follows:

Step 1. Objective function of to-be-solved problem is determined. The objective function is converted into fitness function. The function is nonnegative. In addition, the value should be maximized under any condition [16].

Step 2. Individuals of genetic algorithm population are encoded. Algorithm should be used to initialize the population.

Step 3. Copy operation is implemented according to each individual fitness value to form temporary set C of N individuals.

Step 4. Individual fitness value is calculated, and the fitness function is individually assessed.

Step 5. The crossover operator is acted on the population. Crossover probability is calculated according to formula (15). Two individuals of the population are randomly selected, and new crossover probability is adopted for cross matching and generating two new individuals;

Step 6. Population mutation operator is acted on the population. Mutation probability is calculated according to formula (16). Gene mutation operation is implemented on individuals after matching. Thereby obtaining new individuals:

Step 7. $i = i + 1$ is set for each circulation. The above steps are repeated until $i = T_{\max}$ and algorithm operation is stopped.

5. **Operation results and analysis.** IAGA in the paper, SGA and the AGA are used for cotton assorting parameter optimization solution on the cotton assorting process objective functions $Z(x)$ in order to test the effectiveness of improved adaptive genetic algorithm in cotton assorting process. Genetic algorithm model is built under Mat lab

environment [16]. The algorithm population size is 100. The maximum number of iterations is 200. The search space dimension quantity is 8, and the improved adaptive genetic algorithm crossover probability is set according to formula (15). Improved adaptive genetic algorithm mutation probability is adjusted according to formula (16). Crossover probability and mutation probability values are intimated with evolution generation. The scope is valued within a certain scope. Several experiments are carried out randomly, and the simulation results are shown in table 2.

Table 2. Comparison results of IAGA with other algorithms

Algorithm	Percentage of cotton Xi(%)($i = 1, 2, 3, \ldots, 8$)								Algebra	Optimal value
	X1	X2	X3	X4	X5	X6	X7	X8		
SGA	6.89	12.04	11.97	4.74	16.86	25.47	13.88	8.14	91	1.7277
	4.58	12.49	6.72	8.77	17.47	27.87	13.76	8.36	168	1.7283
	5.86	10.58	10.35	9.95	16.05	27.54	11.97	7.7	152	1.7295
AGA	6.13	13.35	11.18	2.13	17.32	27.90	13.96	8.05	94	1.7261
	6.35	11.87	11.88	5.18	15.81	27.50	13.52	7.9	75	1.7275
	6.86	10.92	10.13	5.11	16.91	27.66	13.95	8.45	100	1.7265
IAGA	7.09	11.88	10.09	1.33	17.86	27.87	15.28	8.6	72	1.7248
	7.32	12.62	11.36	0.2	17.07	27.55	15	8.87	10	1.7244
	6.84	13.39	11.31	1.05	17.11	27.72	13.69	8.9	49	1.7249

Table 2 shows that parameter optimization generations of IAGA are prominently lowered compared with SGA and AGA. Cotton assorting cost is further reduced. The above three genetic algorithms are used for randomly implementing five cotton assorting experiments on cotton assorting process objective function Z(x) at the same time in order to verify the validity of the algorithm in this paper more objectively. The optimal and average value solutions in the five cotton assorting experiments are counted. The operation simulation results are shown in Table 3 and Table 4.

Table 3. Comparison results of optimization I

Algorithm	Optimal value when runs 5 times									
	Algebra	Cost	Percentage of cotton Xi(%) ($i = 1, 2, 3, \ldots, 8$)							
			X1	X2	X3	X4	X5	X6	X7	X8
SGA	120	1.7271	5 .84	12.4	10.97	3.52	16.87	27.76	15.20	7.43
AGA	50	1.7258	6.77	11.34	9.98	2.8	18.03	27.88	15.21	8.0
IAGA	10	1.7244	7.32	12.62	11.36	0.2	17.07	27.55	15.0	8.87

Table 4. Comparison results of optimization II

Algorithm	Average value when runs 5 times	
	Algebra	Cost
SGA	130	1.7281
AGA	83	1.7263
IAGA	41	1.7247

Table 3 and Table 4 shows that the optimal value and average value results of three different algorithms and five operations are compared. IAGA in the paper has good optimization results. The best optima value of cotton assorting cost is 1.7244 million (yuan/ton),and the average value is 1.7247 million (yuan/ton), which are both better than SGA (1.7271 million (yuan/ton), 1.7281 million (yuan/ton)), and the AGA (1.7258 million (yuan/ton), 1.7263 million (yuan/ton)).

The evolution generation refers to the optimization generation of reaching the final value 5% error scope for the first time based on some algorithm in automatic cotton assorting process. The average values of five operations are compared, the solution generation average value of the improved adaptive genetic algorithm is 41. The solution generation average value based on SGA and AGA is 130 and 83. It is obvious that IAGA has faster convergence speed. Compared with SGA, average cotton assorting cost person can be saved by 30 – 35 yuan in the IAGA compared with SGA in the five simulation operations. The cotton assorting cost also can be saved by about 15 – 20 yuan per ton compared with AGA. It is obvious that the cotton assorting cost of algorithm can be further reduced by using the IAGA.

The optimization solution simulation results of three different algorithms on cotton assorting process objective functions $Z(x)$ are shown in Figure 1, Figure 2 and Figure 3.

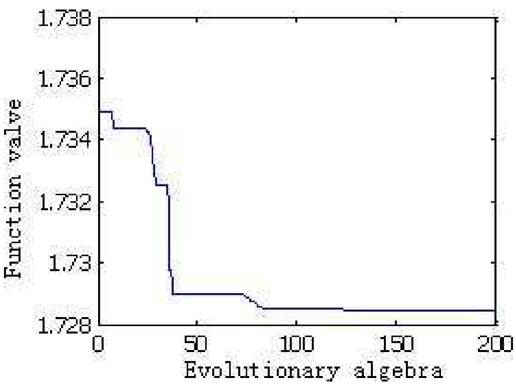

FIGURE 1. The SGA simulation

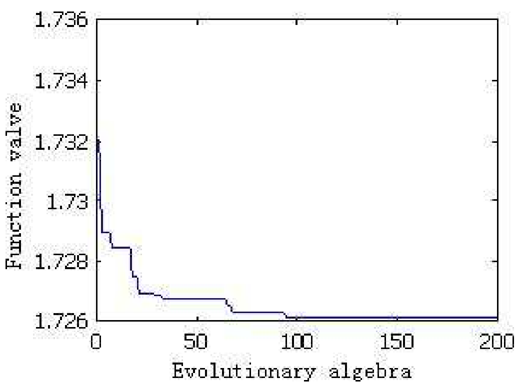

FIGURE 2. The AGA simulation

The IAGA diagram in Figure 3 is compared with simulation curve in Figure 1 and Figure 2. It can be seen that the SGA of Figure 1 can be easily trapped in local solution process in the optimal solution process. Optimal solution process can be completed after repeated shocks for many times. Although AGA in figure 2 is improved on the basis of Figure 1, the effect is still not ideal. Control strategy closely related to evolution generation is applied in IAGA. In the cotton assorting process optimal solution, the descending speed of objective function value $Z(x)$ is accelerated at the initial stage. Next, it enters automatic optimization and stabilization stage quickly. Compared with SGA and AGA, the evolution generation is obviously decreased, it is obvious that system global optimization searching ability can be prominently improved in IAGA, and the cotton assorting cost should be further saved [17].

In order to objectively verify the effectiveness of IAGA, The other advanced algorithm such as Particle Swarm Optimization (PSO) algorithm is used to carry out automatic cotton matching work under the same technical indicators model in Table 2. The PSO algorithm realizes the search task for the optimal solution in complex space mainly through the competition and collaboration among individuals. In the simulation experiments, the size of the group and the maximum number of iterations were all 100, the dimension of search space was 8, the standard PSO algorithm was 1, and the simulation learning factors c1 and c2 were 2. The simulation of the standard PSO algorithm for the solution of the cotton matching target function $F(x)$ is shown in Figure 4.

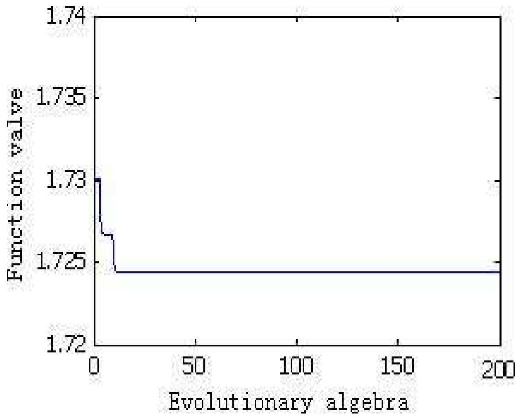

FIGURE 3. The IAGA simulation

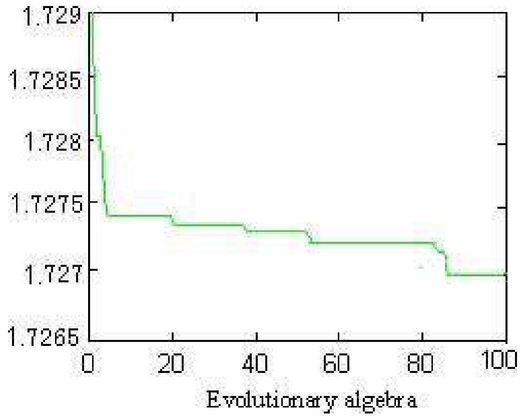

FIGURE 4. The PSO simulation

We can find that the algebraic convergence value of IAGA is 10 in Figure 3 , and the algebraic convergence value is 85 in Figure.4, which shows that IAGA converges is faster. The cost of PSO algorithm is 1.727 (10000 yuan/ton). The cost of IAGA is 1.7249 (10000 yuan/ton), which means that the cost of cotton blending is lower.

It is obvious that the algorithm in the paper has great advantages compared with manual cotton assorting. It can make up the problem in cotton assorting process, which is caused by simply depending on experience and manual operation [18]. Annual productivity of 4000 tons in a cotton spinning factory is adopted for calculation. The IAGA is utilized for comparing to standard genetic algorithm cotton assorting and conventional adaptive genetic algorithm in cotton assorting process parameter optimization. Cotton assorting cost can be saved by nearly 100 thousand yuan or so for the whole year. Enterprise production management efficiency and management profits can be greatly improved.

6. **Conclusion.** In the paper, automatic cotton assorting process model is established. On the basis, improvement strategies are proposed on the above genetic algorithm aiming at the disadvantages of standard genetic algorithm and conventional adaptive genetic algorithm in textile cotton assorting process parameter optimization. The improved adaptive genetic algorithm is utilized in automatic cotton assorting optimal solution. The results show that improved adaptive genetic control strategies proposed in the paper are applied in cotton assorting process parameter optimization. It is in line with related requirements of automatic cotton assorting process. The cotton assorting procession can be further improved. Speed can be further accelerated. Cotton assorting cost can be lowered, product quality and operation profits are improved, and operation theory basis is provided for a existing process optimization in the textile cotton assorting process production with certain reference significance.

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