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Research on Multi-objective Balancing Optimization of Truck Mixed Assembly Line Based on Improved Genetic Algorithm

Kun Yang*, Shuaipeng Wu**, Yibo Wang***and Jian Zou****

Keywords : Mixed flow assembly line, Multi-objective optimization, Genetic algorithm, Assembly line balancing, Flexsim.

ABSTRACT

A corresponding multi-objective mathematical model has been established to address the issue of low production capacity in the mixed-model assembly line of a certain automobile company for trucks. The problems of slow convergence speed and easy entrapment in local optimal solutions of the standard genetic algorithm are addressed by improving the genetic algorithm. Selecting examples from the literature to test the performance of the improved genetic algorithm had been done, and Matlab had been used for programming and solving. The results showed that the workload decreased from 0.653 to 0.513, worker costs dropped from 1,872 yuan to 1,786 yuan, and the operation time of the improved genetic algorithm was reduced by 37%. A mixed-model assembly line simulation was created using Flexsim simulation software. The results indicated that the disparity in utilization rate among workplaces decreased to 12.25%, and production output increased from 1,000 units to 1,190 units. The balance optimization was carried out for a specific truck assembly line. The results indicate that the number of workplaces decreased from 26 to 23, the workload dropped from 15.36 to 11.27, and worker costs fell from 7,138 yuan to 6,257 yuan. These findings suggest that the selected optimization objectives and the improved genetic algorithm are effective in addressing multi-objective balancing problems in mixed-model assembly lines.

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** Associate Professor, College of Mechanical Engineering and Automation, Liaoning University of Technology, Jinzhou, 121000, China.*
*** Graduate Student, College of Mechanical Engineering and Automation, Liaoning University of Technology, Jinzhou, 121000, China.*
**** Lecturer, College of Mechanical Engineering and Automation, Liaoning University of Technology, Jinzhou, 121000, China.*
***** Laboratory Master, College of Mechanical and Power Engineering, Yingkou Institute of Technology, 115014, China*

INTRODUCTION

An automobile company utilizes a mixed-model assembly line to produce various truck models. This approach allows for the simultaneous production of different types of products and enables a rapid response to market changes. It can effectively minimize unnecessary investments and reduce production costs for the enterprise. However, when using the mixed-model assembly line, the automobile company faces balance issues associated with it. An improper assignment of tasks can result in wasted working time during the assembly process. This inefficiency may lead to an increased number of workplaces needed, a low assembly line balance rate, and an uneven distribution of workload among the places. Hence, achieving balance in the mixed-model assembly line is essential, as it directly impacts the production efficiency of the enterprise. Numerous scholars and researchers around the world have studied issues related to assembly lines. J. Chen proposed a novel bi-level multi-objective genetic algorithm (NBMGA) that treats assembly line balancing (ALB) and part feeding (PF) as an integrated problem. Through a series of computational experiments, the study demonstrated the effectiveness of genetic algorithms in addressing balancing problems for mixed-model assembly lines. Pan L. studied optimization methods for cement clinker production lines. By utilizing BP neural networks and genetic algorithms (GA) to optimize the operational parameters in cement plants, the findings demonstrated that the combination of the neural network and GA significantly improved the efficiency of the production line and effectively tackled operational challenges. Krenczyk discussed the balancing challenges faced by modern assembly lines in the automotive industry, particularly for large-scale products. He proposed a model aimed at solving the multi-person assembly line balancing problem. In this

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model, assembly tasks were assigned to specific areas that closely corresponded to where the tasks would be performed on the vehicle. A hybrid method was proposed that combined an enhanced heuristic algorithm for assigned tasks with boundary and backtracking techniques. This method was employed to determine task assignments for workers. KY Li presents a novel method that integrates stable diffusion-based Generative AI with computer-aided design automation to minimize data requirements while maintaining high design accuracy. This research provides a scalable solution to the challenges of generative design in data-limited settings and contributes to advancing intelligent design systems across various engineering sectors. M Li designed a hybrid genetic algorithm and constructed to combine three evaluation metrics: the smoothing index, the equilibrium loss coefficient and the imbalance coefficient of the adaptation function, combining the simulated annealing algorithm with a genetic algorithm to speed up convergence to obtain a global optimal solution. It demonstrates that the method is suitable for solving balance problems in mixed-flow assembly lines. Gu Wenyu and his team focus on enhancing machine tool utilization rates while decreasing blocking rates in flexible production lines. This objective led to the development of a production line allocation method integrating genetic algorithms with Flexsim simulation software. The combination of genetic algorithm calculations and Flexsim simulations enabled result analysis and the proposal of targeted improvement measures. These optimizations substantially boosted enterprise productivity. Existing research on mixed-model assembly line balancing mainly focuses on single-objective optimization. Although various algorithms have been developed to address this problem, the solutions typically optimize from only one perspective, which results in a lack of comprehensive balance in mixed-model assembly lines. While some studies have explored multi-objective approaches, their research objectives are still not sufficiently comprehensive. Achieving true assembly line balance is currently unattainable with existing methods. This study addresses this challenge by developing an objective function that minimizes both the number of workplaces in mixed-model assembly lines and the associated processing costs of products. The proposed function aims to optimize production takt time and balance workload between workplaces. By thoroughly analyzing the constraints of the objective function, we achieve greater adaptability to market demands and increased practical value for mixed-model assembly lines. The study presents a population expansion mechanism designed to enhance the algorithm's global optimization capabilities. In this approach, the probabilities for crossover and mutation are dynamically adjusted based on variations in fitness values and the number of evolutionary generations. This methodology effectively protects high-quality individuals from being eliminated. Verification through benchmark cases from existing literature demonstrates that the enhanced genetic algorithm outperforms traditional methods, showcasing its superior performance and effectiveness. The enhanced mixed-model assembly line simulation model was developed using Flexsim simulation software. The results of the simulation confirm the effectiveness of the improved genetic algorithm in addressing the challenges of mixed-model assembly line balancing. After validating performance, the application of this enhanced algorithm to optimize a truck manufacturer's mixed-model assembly line demonstrates its practical utility for balancing automotive production lines. The outcomes of this implementation highlight the significant value of applying the proposed genetic algorithm to balancing truck assembly lines in the automotive sector.

ESTABLISHMENT OF MATHEMATICAL MODEL FOR MULTI-OBJECTIVE BALANCE PROBLEM OF MIXED-MODEL ASSEMBLY LINE

Problem description and hypothesis

The balance problem of the truck mixed-model assembly line in the automobile company studied can be described as: Comprehensively considering the job priority relationships of trucks A, B, and C for sorting, under the premise of meeting the job priority processing relationships and various constraints. All processes are reasonably distributed to various workplaces, which balances the load of all workplaces and enhances the production efficiency of the assembly line. By doing so, it also reduces the number of workplaces and labor costs, further improving the overall operational efficiency. It is a multi-objective optimization problem.

The company's mixed-model assembly line simultaneously assembles three types of trucks, A, B, and C, which are similar in terms of technology and structure. The daily total demand for the three types of trucks is 140 units, with the corresponding demand ratios for the three types of trucks being 0.5, 0.3, and 0.2, respectively. The general assembly line for the trucks has 26 workplaces, and 72 processes are assigned to them. The tasks and assembly times for the three types of vehicles on the mixed-model assembly line are shown in Table 1.

Tab 1. Tasks and Operating Time of Truck Mixed-model Assembly Line (Unit: Seconds)

Job serial number	Job tasks	TA	TB	TC
1	Truck frame allocate to the assembly line balance frame and install	130	140	130

2	Assemble valve body for controlling gear oil pressure	36	38	36
3	Install the thrust rod on the balance frame	73	75	72
4	Install springs for damping performance	85	85	85
5	Install a U-shaped bolt for fixing on the spring.	30	33	30
6	Tighten bolts, make sure no gap between bolt and spring	43	43	43
7	Add lubricating oil to bolts and springs.	15	15	20
8	Install the direct reaction lever	150	150	150
9	Put the tube bundle on the plastic tube and tighten the tube bundle.	180	190	186
10	All vehicular wiring must be securely mounted onto the wire harness to prevent detachment during operation.	170	170	150
11	Install a tank for holding urea solution	60	60	60
12	Arrangement of air pipes in the car	30	30	35
13	The deployment bracket is used to support the rear axle air storage tank	100	100	100
14	Adjust the transmission shaft to ensure that there is no deviation	310	310	310
15	The deployment bracket is used for supporting the silencing device	162	165	160
16	Adjust the middle bridge to ensure that there is no deviation in position	150	154	155
17	Deploy the stopper and fix its position	95	95	100
18	Deploy and fix the front axle spreader	15	15	15
19	Deploy and fix the vibration damping device	55	55	80
20	Adjust the front axle to ensure that there is no deviation in position	160	160	160
21	The deployment bracket is used for supporting the longitudinal tension rod	65	65	60
22	Deploy clutch booster cylinder	35	35	40
23	The deployment transmission shaft is connected with the rear axle	118	110	0
24	Adjust the rear axle to ensure that there is no deviation in position	110	115	120
25	Deploy the stabilizer bar and fix it	0	0	30
26	Hydraulic lifting pump for vehicle body deployment	54	54	65
27	The deployment bracket is used to support the gearbox	88	96	60
28	Deploy the suspension bracket in the driving position of the front of the vehicle	18	18	89
29	Deploy the cross member above the driving position	0	0	36
30	Electric device for adjusting differential lock	80	80	80
31	Deploy the pneumatic horn of the truck and fix it	6	6	6
32	The deployment bracket is used to support the air filter	24	24	12
33	Prepare special steel plates and install them at the front axle	18	18	18
34	Deployment of spare tire lifting device	140	140	150
35	The deployment bracket is used to support the rear axle.	145	145	142
36	The deployment bracket is used to support the exhaust device	0	0	35
37	Mark the frame number	160	160	160
38	The deployment bracket is used to support the engine	60	60	30
39	Fixing frame for deploying battery	60	60	60
40	The deployment bracket is used for supporting the heat dissipation device	95	95	95
41	The deployment bracket is used to support the fuel tank	90	90	90
42	Start the overturning device to overturn the truck frame	220	220	206
43	Adjust the brake device and fix it	60	60	54
44	Adjusting steering device	130	130	130
45	Post-processor device for allocating truck position	95	95	90
46	Prepare special heat insulation film	80	80	60
47	Arrangement of steering oil pipeline	105	105	103
48	Arrangement of air conditioning pipes	80	83	86
49	Clamping thrust rod	60	60	70
50	Dispose stamping saddle	0	0	35
51	Deploy the engine and fix it	260	260	260
52	Deploy the heat sink and fix it	72	72	72
53	Deploy air filter	170	170	165
54	Deploy and fix the silencer	135	135	135
55	The deployment pin shaft is used to fasten the cab	150	150	150
56	Deploy special protective beams and fix them	160	160	160
57	Deploy the cab and fix it	320	320	320
58	Arrangement of lifting oil pipeline in driving position	35	36	39
59	Filling hydraulic oil	120	115	100
60	Connect the arranged chassis pipeline	180	180	176
61	The deployment bracket is used to support the lamp	50	50	50
62	Blend tires	278	278	278
63	Prepare the spare tire and fix it on the spare tire bracket	90	90	0
64	Dispose the battery in the battery frame	15	15	15
65	Tighten the bolts at the tire	150	150	150
66	Dispose the lamp at the lamp bracket	125	125	150
67	Deploy large fuel tank of the truck	35	35	35
68	Deploy the left bumper of the truck	75	75	75
69	Deploy the right bumper of the truck	65	65	65
70	Deploy the front of bumper of the truck	65	65	100
71	Air tightness test of the truck pipeline	130	130	130
72	Overall inspection of the truck	120	120	135

To ensure that the optimization model is effective for practical production application, the following assumptions are made on this issue:

(1)The same product assembly tasks should be performed within the same workplaces;

(2)Draw the priority diagrams for the operation sequence of each product, and synthesize the priority relationships of the operation tasks of each product into a comprehensive priority diagram for the job sequence;

(3)Determine the assembly time for each job task, and ensure that the same job tasks are assigned on the assembly line for different products;

(4)The comprehensive operation time at each workplace must be less than the set production rhythm, and there are no parallel workplaces on the assembly line.;

(5)The types of products assembled on the mixed-model assembly line are different, but the assembled products share the same technology and structure.

Mathematical model

Constraint condition：

$$\sum_{\mathrm{n}=1}^{N} n x_{in} \le \sum_{\mathrm{n}=1}^{N} n x_{jn} \tag{1}$$

$$\sum_{n}^{N} x_{in} = 1 \tag{2}$$

$$\sum_{n=1}^{N} y_{dn} = 1 \tag{3}$$

$$T_n \le CT_{theory} \tag{4}$$

Formula (1) is a constraint condition to follow the priority relationship of work tasks, where N is the total number of workplaces, n is the number of workplaces $n=1, 2, 3, ..., N$, and I is the number of product work tasks $i = 1, 2, 3, ..., I$. Formula (2) restricts that a task can only be assigned to one workplace. Formula (3) constrains that only one worker is arranged on a workplace, where d is the worker number $d = 1, 2, 3, ..., D$. Formula (4) is used to constrain that the total assembly time of the tasks assigned to each workplace must be less than or equal to the theoretical rhythm, where CT_{theory} is the theoretical production rhythm of the assembly line, T_{kn} is the product with the product number k, indicating its total operation time at the workplace with the work number n, and T_n is the total time required for the product to be assembled at the workplace with the work number n.

Formula (5) is to optimize the objective function, and allocate workers according to the theoretical minimum number of workplaces to solve the minimum number of workplaces of mixed-model assembly line, where I is the total number of product assembly tasks, K is the total number of products, k is the product number $k=1,2,3,...,K$, M is the total demand of all products in the planning period, and t_{ki} is the product with product number k, and its working time when assembling the task with number i, and M_k is the required quantity of the product with number k. When the calculated minimum number of workplaces is not a whole number, it should be rounded up to the nearest integer using the ceiling function (*ceil*). And, u represents the cumulative count of problem-solving iterations during continuous runtime debugging, where u takes on values of $1, 2, 3, ..., U$.

$$Fit_1 = \min W = Ceil\left(\frac{\sum_{k=1}^{K} m_k \sum_{i=1}^{I} \mathrm{t}_{ki}}{M \times CT_{theory}} \right) + u - 1 \tag{5}$$

Formula (6) is an optimization objective function, which makes the actual production rhythm small enough on the basis of meeting the theoretical production rhythm and the number of workplaces is known, where q_k is the demand ratio of the product numbered k and CT is the actual production rhythm of the assembly line.

$$Fit_2 = \min CT = \min\left(\sum_{i=1}^{I} \sum_{k=1}^{K} q_k x_{in} t_{ki} \right) \tag{6}$$

Formula (7) indicates that each workplace can only be assigned one worker, meaning the number of workplaces is equal to the number of workers. If worker d and task i are assigned to workplace n, then the total assembly cost for worker d at workplace n is denoted as C_d, where C_{di} is the assembly cost of the worker d processing the task i, x_{in} and y_{dn} are decision variables, $x_{in}=0$ is that the task i is not assigned to the workplace n, $x_{in}=1$ is that the task i is assigned to the workplace n, and $y_{dn}=0$ is that the worker d is not assigned to the workplace n, $y_{dn}=1$ is that the task i is assigned to the workplace n.

$$C_d = C_{di} y_{dn} x_{in} \tag{7}$$

Formula (8) is the optimization objective function, which represents the total worker cost of mixed-model assembly line, and D is the sum of the number of workers to be equipped on the assembly line.

$$Fit_3 = \min COST = \sum_{n=1}^{N} \sum_{d=1}^{D} \sum_{i=1}^{I} \left(C_{di} y_{dn} x_{in} \right) \tag{8}$$

Formula (9) is the optimization objective function, and to keep the working time of each workplace consistent, the load balance index SI of each workplace is used to judge, that is, the variance of the weighted value of assembly time of each workplace is taken, and the load balance index SI of each workplace should be as small as possible while meeting the production rhythm.

$$Fit_4 = \min SI = \sqrt{\frac{\sum_{n=1}^{N}\left(\sum_{k=1}^{K}\sum_{i=1}^{I} q_k x_{in} t_{ki} - \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{i=1}^{I} q_k x_{in} t_{ki} / N\right)^2}{N}}$$

(9)

AHP (Analytic Hierarchy Process) is used to calculate the weights of three objectives: actual production rhythm, total worker cost and workplace load. Because the number of workplaces is minimized through continuous debugging, the goal of the number of workplaces W is not weighted. Through on-the-spot visits and inquiries from enterprise experts, the order of importance of influencing factors of assembly efficiency on assembly line is: actual production rhythm > workload between workplaces > total worker cost. The multi-objective judgment matrix of assembly line is constructed as shown in Table 2.

The weight ω1 of actual production rhythm *CT*, the weight *ω2* of total worker *COST* and the weight *ω3* of workload *SI* between workplaces are obtained by power method.

Tab 2. Multi-objective judgment matrix of assembly line

Target	Actual production rhythm	Total worker cost	Workload between workplaces
Actual production rhythm	1	3	5
Total worker cost	1/5	1/2	1
Workload between Workplaces	1/3	1	2

According to the judgment matrix, the weights of actual production rhythm, total worker cost and load between workplaces are *ω1=0.6483*, *ω2=0.1220* and *ω3=0.2297*, respectively.

$$Fit = Fit_1 + 0.6483 Fit_2 + 0.1220 Fit_3 + 0.2297 Fit_4$$

(10)

IMPROVED GENETIC ALGORITHM DESIGN FOR MULTI-OBJECTIVE BALANCE OPTIMIZATION OF MIXED-MODEL ASSEMBLY LINE

Improved design of genetic algorithm

This section describes the improved design of the genetic algorithm, including the following steps:

(1)Encode

The priority relation diagram of job sequence is shown in Figure 1. According to the priority relation of job tasks sequence, 12 job tasks can be arranged in a row as shown in Figure 2, and each job task is the position of a gene on the chromosome.

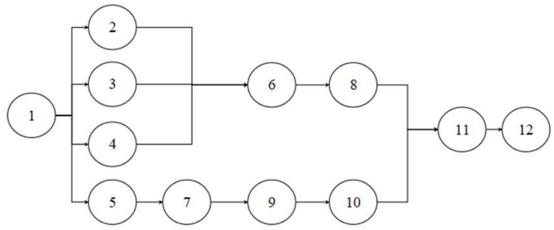

Fig. 1. Job order priority relationship diagram

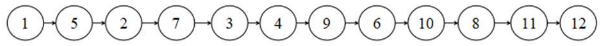

Fig. 2. Gene coding of task

(2)Generate initial population

Topological sorting theory and random search method are used to generate the initial population, and the operation steps are as follows.

It is assumed that the set of job tasks on the assembly line is $TS_1=\{ts_1, ts_2, ts_3, ..., ts_i\}$, and the job tasks can be represented as $i=1, 2, 3, ..., n$.

Based on the priority diagram of job tasks, select any task from the set *TS* that either has no immediate preceding task or whose preceding task has already been assigned, and place it into the set TS_1. At the same time, delete the process logic sequence related to the selected job task in the priority diagram.

3) Select any job task from the set TS_1, identify the corresponding gene position, and place it accordingly.

4) When the set of assembly tasks $TS_1=\{ts_1, ts_2, ts_3, ..., ts_i\}$ is determined to be empty ($TS_1=\varnothing$), it indicates that the assembly tasks have been assigned to the workplaces. If not, repeat step 2.

(3) Decode

When calculating the fitness value of chromosomes, firstly, the coded chromosomes are segmented according to the requirements of optimization objectives, and the assignments assigned to each workplace are obtained. The specific operation process is as follows.

Set the initial production rhythm, and determine the quotient according to the total operation time *T* and the total number of existing workplaces *n*, that is, $CT_{theory}=T/n$.

Taking CT^* as the rhythm, and taking the priority diagram of operation sequence as the standard, the actual operation tasks are reasonably arranged in *n* workplaces. If we can get the time $T_n \leq CT^*$ for each work place, it means that CT^* is the minimum production rhythm after gene sequencing, and it is necessary to stop the iterative operation process, but when $T_n \geq CT^*$, continue the next operation.

Complete the calculation of the potential increments $\Delta 1, \Delta 2, \Delta 3, ..., \Delta n$ of the workplace on the actual assembly line.

Let $CT=max\{Tk\}$, $CT^*=min\{Tk+\Delta n\}$, if $CT \leq CT^*$, stop the search, otherwise, return to step 2.

(4)Fitness function

To address the issue of varying quantization scales and units among different targets, it is essential to normalize the data and scale it to a 0-1 interval. This step ensures the comparability of the data. Linear function normalization is utilized to process the data on the assembly line, thereby standardizing the input data. The mathematical model of the objective function is adopted as the fitness function, as indicated in formula (10). The linear function normalization is applied to the original data to ensure it falls within the [0-1] range, with the specific calculation method presented in formula (11). In this context, X_{max} represents the maximum value within the data set, while X_{min} signifies the minimum value.

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{11}$$

(5)Select

Both elite selection and roulette wheel selection are used. Let the population size be n, the fitness value of individual i be $Fit(i)$, and the selected probability P_i is defined as Formula (12).

$$P_i = \frac{Fit(i)}{\sum_i^n Fit(i)} \tag{12}$$

(6)Intersect

Selects the intersection of two points, and the operation steps are as follows.

Randomly select any two chromosomes (parent 1 and parent 2) from the population as a gene string consisting of n genes for crossover.

Taking parent 1 and parent 2 as objects, two crossing points β1 and β2 are randomly selected and satisfy $1<\beta1<\beta2<n$, and the two parent chromosomes are divided into three parts: head, middle and tail.

The middle section of parent 1 is extracted and rearranged according to the order of the genes in the corresponding section of parent 2, and then the rearranged genes are placed back into the middle of parent 1. Similarly, the middle section of parent 2 is extracted and rearranged according to the order of the genes in the corresponding section of parent 1, and the rearranged genes are also placed back into parent 2. The specific steps of the two-point crossover are shown in Figure 3.

	Head				β_1 Middle				β_2 Tail			
Parent 1	1	4	2	5	3	6	7	8	10	9	11	12
Parent 2	1	3	2	5	4	7	6	11	10	9	8	12

Fig. 3. Selection of crossing point

In parent 1, two crossover points are randomly selected, and the genes in the middle section are chosen. The middle part of parent 1 is shown in Figure 4. The sequence of genes 3, 6, 7, and 8 is identified from parent 2, and this arranged gene sequence is taken as the middle part of parent 1, as depicted in Figure 5. Similarly, a new gene sequence for the middle part of parent 2 can be obtained, as shown in Figure 6. The chromosomes of progeny 1 and progeny 2 after the two-point crossover are illustrated in Figure 7.

3	6	7	8

Fig. 4. The sequence of genes in the middle part of parent 1

3	7	6	8

Fig. 5. New gene sequence in the middle part of parent 1

4	6	7	11

Fig. 6. New gene sequence in the middle part of parent 2

	Head				Middle				Tail			
progeny 1	1	4	2	5	3	7	6	8	10	9	11	12
progeny 2	1	3	2	5	4	6	7	11	10	9	8	12

Fig. 7. Crossed offspring chromosomes

(7)Mutation

The mutation operation steps of the genetic algorithm are as follows.

Select a chromosome randomly to serve as the parent chromosome;

Randomly select a mutation point on the parent chromosome;

Delete the gene before the mutation point, regenerate a gene segment, and finally get a brand new chromosome.

The four positional genes retain their original state, while the eight genes following the mutation point undergo recombination based on the actual operational sequences, resulting in the formation of a novel chromosome (see Figure 8). Figure 9 illustrates the priority relation matrix for gene positions affected by the mutation. By randomly selecting sortable jobs (for example, gene 7), Figure 10 shows the updated priority matrix. To provide a clearer visualization of the chromosomal changes before and after the mutation, Figure 11 presents a comparative display of both states.

				Mutation point							
1	4	2	5	3	6	7	8	10	9	11	12

Fig. 8 Recombinant gene map

Genes

	3	6	7	8	10	9	11	12
3	0	1	0	0	0	0	0	0
6	0	0	0	1	0	0	0	0
7	0	0	0	0	0	1	0	0
8	0	0	0	0	0	0	1	0
10	0	0	0	0	0	0	1	0
9	0	0	0	0	1	0	0	0
11	0	0	0	0	0	0	0	1
12	0	0	0	0	0	0	0	0

Fig. 9 Priority matrix diagram of remaining genes

Genes

	3	6	8	10	9	11	12
3	0	1	0	0	0	0	0
6	0	0	1	0	0	0	0
8	0	0	0	0	0	1	0
10	0	0	0	0	0	1	0
9	0	0	0	1	0	0	0
11	0	0	0	0	0	0	1
12	0	0	0	0	0	0	0

Fig. 10 The updated priority relation matrix graph

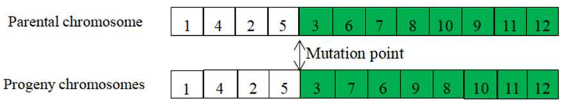

Fig. 11 Gene comparison map before and after mutation

(7)Adaptive crossover and mutation probability

The probability of adaptive crossover and mutation is as follows:

$$P_c = P_{c\max} - \frac{(P_{c\max} - P_{c\min})(Fit_c - Fit_{avg})}{Fit_{\max} - Fit_{avg}} \tag{13}$$

$$P_c = P_{c\max} \tag{14}$$

$$P_m = P_{m\max} - \frac{(P_{m\max} - P_{m\min})(Fit_m - Fit_{avg})}{Fit_{\max} - Fit_{avg}} \tag{15}$$

$$P_m = P_{m\max} \tag{16}$$

When $Fit_c \geq Fit_{avg}$, as shown in Formula (13). When $Fit_c < Fit_{avg}$, as shown in Formula (14). When $Fit_m \geq Fit_{avg}$, as shown in Formula (15). When $Fit_m < Fit_{avg}$, as shown in Formula (16). In formulas (14) and (15), Fit_{max} is the maximum fitness value; Fit_{avg} is the average fitness among individuals; The individual fitness value of Fit_c used in crossover operation is large; Fit_{ness} value of Fit_m for mutation operation; P_{cmax} and P_{mmax} represent the maximum crossover and mutation probability, and P_{cmin} and P_{mmin} represent the minimum crossover and mutation probability respectively.

EXPERIMENTAL VERIFICATION

Algorithm performance test

To verify the performance and effectiveness of the improved genetic algorithm, an actual mixed-model assembly line from literature is first selected. The improved genetic algorithm is then applied to solve and verify the mixed-model assembly line.

In the literature, two different types of products are assembled on the same assembly line. There are a total of 25 tasks for the two products, which are assigned to 13 workplaces. The production cycle is set at 94 seconds, and the assembly times for the products in processes 4, 23, and 25 exceed 94 seconds. Two workers are assigned to operate, with the demand for product A and product B being 400 and 600, respectively. The priority relationship of each job task on the mixed-model assembly line is illustrated in Figure 12.

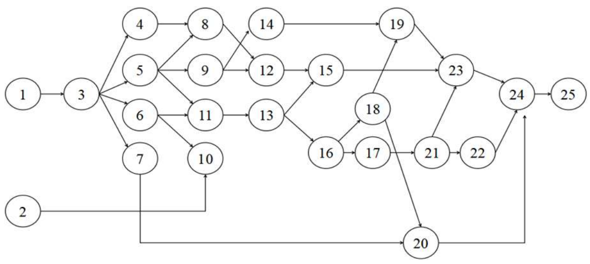

Fig. 12 Priority diagram of integrated operation process of mixed-model assembly line

For products A and B, the operation time of all processes in each workplace is shown in Table 3.

Tab 3. Processing time of two different types of products A and B(Unit: Seconds)

Number i	tA	tB	Number i	tA	tB
1	0	20	14	13	0
2	77	77	15	55	55
3	73	73	16	19	20
4	150	150	17	37	0
5	88	88	18	94	94
6	62	0	19	13	13
7	36	0	20	0	90
8	0	20	21	20	20
9	66	66	22	47	47
10	25	25	23	96	82
11	55	55	24	41	37
12	71	71	25	125	0
13	59	59			

The worker costs of all workers in assembling different workplaces are shown in Table 4.

Tab 4. Worker costs required for different tasks(Unit: yuan)

Task	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12	m13
1	19	28	32	16	21	33	27	67	35	42	29	56	41

2	18	36	27	26	31	15	19	26	14	32	22	37	51
3	26	31	78	65	35	42	37	28	39	19	28	44	64
4	26	43	37	66	19	58	33	72	49	52	33	27	53
5	48	55	35	27	59	43	16	78	55	74	28	31	58
6	35	44	61	38	16	11	37	54	47	25	43	19	43
7	36	29	18	53	32	14	22	25	68	37	41	54	39
8	22	48	34	54	36	72	19	16	22	32	18	71	42
9	22	63	33	48	46	66	18	32	51	42	17	37	43
10	13	29	31	28	53	37	16	29	57	43	23	26	38
11	22	35	43	19	28	66	26	37	46	28	49	61	21
12	25	36	49	34	52	19	36	22	43	52	29	37	13
13	28	47	32	23	19	46	51	38	25	64	45	28	19
14	28	43	73	37	53	25	43	54	63	46	51	38	16
15	28	36	45	26	23	31	55	47	56	42	56	18	37
16	23	42	18	37	53	39	48	36	54	33	67	28	35
17	28	55	63	44	46	65	38	25	33	27	18	27	61
18	18	42	53	19	28	36	41	55	29	36	22	18	71
19	28	39	64	24	35	43	19	28	43	28	16	23	45
20	61	36	47	37	22	18	52	46	26	23	13	21	34
21	38	39	31	72	16	36	49	37	42	25	48	72	19
22	54	51	25	45	31	42	50	51	53	19	36	19	18
23	27	48	29	34	25	51	51	24	61	15	47	51	72
24	36	24	41	37	19	26	51	38	26	48	65	36	45
25	48	36	25	22	37	28	53	42	37	36	42	29	34

The improved genetic algorithm is applied to the selected literature cases, and programmed with Matlab R2023a under the Windows 11 system. The improved genetic algorithm includes particular configurations for workforce parameters, in which the population number is 100, the maximum evolutionary algebra is 100 generations. The crossover probability P_c is 0.8, and the mutation probability P_m is 0.05. The minimum crossover probability P_{cmin} is 0.5, the maximum crossover probability P_{cmax} is 0.9, the minimum mutation probability P_{mmin} is 0.005 and the maximum mutation probability P_{mmax} is 0.01. The results of optimization are shown in Figure 13 and Figure 14.

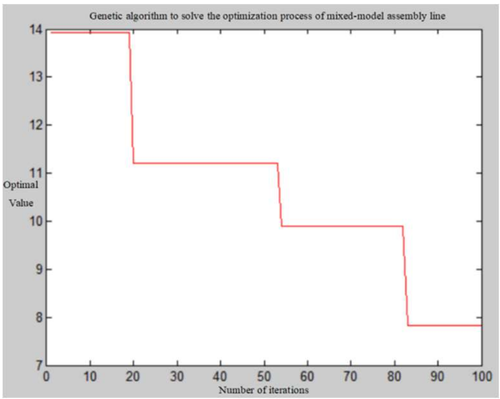

Fig. 13 Genetic algorithm iteration graph

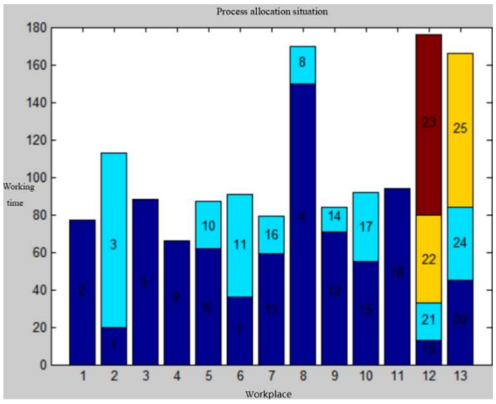

Fig. 14 Process allocation diagram

After 83 iterations, the improved genetic algorithm got the optimal solution. As shown in Figure 15, operation 9 is assigned to workplace 4; operations 6 and 10 are assigned to workplace 5; operations 7 and 11 are assigned to workplace 6; operations 13 and 16 are assigned to workplace 7; operations 4 and 8 are assigned to workplace 8; operations 12 and 14 are assigned to workplace 9; operations 15 and 17 are assigned to workplace 10; and operation 18 is assigned to workplace 11. Workers are then assigned to the corresponding workplaces. The comparison of the optimization results from the literature and the improved genetic algorithm is shown in Tables 5 and 6

Tab 5. Literature optimization results

Workplace	Working procedure	Number of workers	Production rhythms	Workload	worker costs	Running time

1	2	1				
2	1,3	1				
3	5	1				
4	4,7,8	2				
5	6	1				
6	10,11	1				
7	9,14	1	94	0.653	1872	43
8	12	1				
9	13,16	1				
10	18	1				
11	15,17	1				
12	19,21,22,23	2				
13	20,24,25	2				

Tab 6. Literature optimization results

Workplace	Working procedure	Number of workers	Production rhythms	Workload	worker costs	Running time
1	2	1				
2	1,3	1				
3	5	1				
4	9	1				
5	6,10	1				
6	7,11	1				
7	13,16	1	94	0.513	1786	27.3
8	4,8	2				
9	12,14	1				
10	15,17	1				
11	18	1				
12	19,21,22,23	2				
13	20,24,25	2				

The comparison of Tables 5 and 6 shows the improved genetic algorithm's effectiveness in minimizing workload disparities between workplaces, from 0.653 to 0.513, and at the same time, it can effectively reduce the worker cost of workers, and the worker cost is reduced from 1,872 yuan to 1,786 yuan, and the operation time of the improved genetic algorithm is greatly reduced, by (43-27.3)/43=0.37=37%.

Flexsim simulation software simulation

(1)Simulation basic data

Flexsim simulation is carried out for the example in reference 11. In reference 11, the assembly time of two products in each working place on the assembly line and the assembly time in each working place after improving the original assembly line by genetic algorithm are shown in Table 7.

Tab 7. Assembly time on each workplace of the literature and improved assembly line (Unit: Seconds)

	Workplace	Product A	Product B	Workplace	Product A	Product B
Assembly time on each workplace of the assembly line	1	77	77	8	71	71
	2	73	93	9	78	79
	3	88	88	10	94	94
	4	186	170	11	92	55
	5	62	0	12	176	162
	6	80	80	13	166	127
	7	79	66			
Assembly time of each workplace of the improved assembly line	1	77	77	8	150	170
	2	73	93	9	84	71
	3	88	88	10	92	55
	4	66	66	11	94	94
	5	87	25	12	176	162
	6	91	55	13	166	127
	7	78	79			

Due to the different demand for two products A and B, two different types of products A and B need to be assembled on the same assembly line according to a certain mixing ratio, and the demand for two products A and B on the mixed-model assembly line is set at 400 pieces and 600 pieces respectively, as shown in Table 8. According to the effective working time of 8 hours per day, the number of workplaces of mixed-model assembly line before and after improvement is 13.

Tab 8. Demand for two products

Types of products processed	Product A	Product B	Total
Number of products processed	400	600	1000

(2)Simulation results and analysis

The correspondence between simulation entities and their respective entities in the Flexsim simulation model is shown in Table 9. Running the simulation model as shown in Figure 15, you can get the status percentage report of each work place as shown in Table 10 and Table 11.

Tab 9. Correspondence between the simulation entities in the Flexsim simulation model and the entities on the assembly line

Model entities	Role in the Simulation Process	Practical Function
Generator	Raw Material Buffer Zone	Production Commencement
Buffer	Work-in-Process Storage	Avoid Work-in-Process Accumulation
Processor	Representing Individual Workplaces	Actual Manufacturing Site
Absorber	Finished Goods Packaging Area	Manufacturing Completion

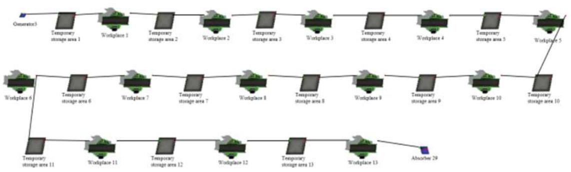

Fig. 15. Simulation layout model of the Flexsim mixed-model assembly line

Tab 10. The state of each workplace before improvement

Object	Processing/%	Idle/%	Blocked/%
1	85.82	14.18	0
2	76.47	23.53	0
3	73.96	26.04	0
4	79.15	20.85	0
5	84.73	15.27	0
6	82.68	17.32	0
7	63.67	36.33	0
8	97.68	2.32	0
9	71.83	28.17	0
10	89.26	10.74	0
11	67.58	32.42	0
12	91.72	8.28	0
13	81.44	18.56	0

Tab 11. The state of each workplace after improvement

Object	Processing/%	Idle/%	Blocked/%
1	96.27	3.73	0
2	97.36	2.64	0
3	89.12	10.88	0
4	97.72	2.28	0
5	94.27	5.73	0
6	96.48	3.52	0
7	88.74	11.26	0
8	94.34	5.66	0
9	89.12	10.88	0
10	97.83	2.17	0
11	86.51	13.49	0
12	98.76	1.24	0
13	97.66	2.34	0

Draw a contrast line chart as shown in Figure 16. As can be seen from Figure 16, after the mixed-model assembly line is optimized by using the improved genetic algorithm designed, the working procedure arrangement on the workplace has changed, and finally the utilization ratio on the workplace has been reduced to 12.25%, which is obviously improved compared with before. Set performance indicators, record the number of absorber inputs and generate data of finished products, as shown in Table 12. It can be seen that the number of products A and B is 465 and 725 respectively, and the output has increased from 1000 to 1190 compared with that before improvement.

Tab 12. Demand for two products

Product	A	B	Total
Current product demand	465	725	1190

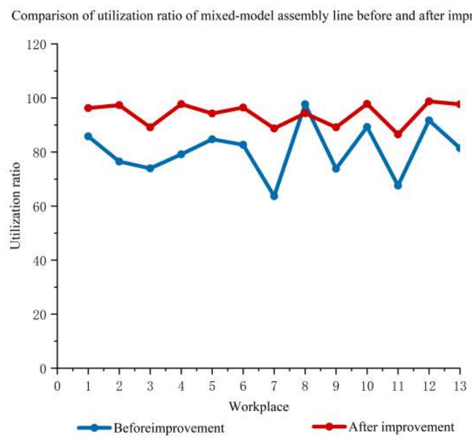

Fig. 16 Comparison chart of utilization rate of each workplace

Table 13 presents the statistical analysis comparing the performance of algorithms before and after optimization, based on Flexsim simulations. The results show statistically significant improvements across all key metrics. The workload imbalance index decreased from 0.653 (±0.042) to 0.513 (±0.031), which represents a 21.4% reduction along with a significantly tighter variance (F-test, $p < 0.05$). In terms of computation time, the 95% confidence interval for improvement ranged from 13.1 to 18.6 seconds, with non-overlapping ranges between the two methods, confirming robust significance. Most importantly, the effect size for time reduction was found to be Effect Size d = 1.72, greatly exceeding the 0.8 threshold for large practical significance. This indicates that the optimization provides both statistical and operational value to production systems.

Tab 13. Statistical Analysis of Algorithm Performance

Metric	Standard GA	Improved GA	Improvement	Statistical Significance
Iterations to converge	120 ± 15.2	83 ± 9.7	30.8%	p=0.003
Workload imbalance index	0.653 ± 0.042	0.513 ± 0.031	21.4%	95% CI
worker cost	1872 ± 68.5	1786 ± 52.3	4.6%	p=0.012
Computation time	43 ± 3.1	27.3 ± 2.4	37%	Effect size d=1.72

CASE ANALYSIS

The improved genetic algorithm has proven to be effective in solving the balance problem of mixed-model assembly line by algorithm performance verification and Flexsim simulation software simulation verification. Now, the balance optimization of truck mixed-model assembly line of an automobile company is carried out, and further validate the effectiveness of the improved genetic algorithm over time.

Considering the operation priority relations of three kinds of trucks, A, B and C, the priority relations of the three kinds of trucks are sorted, and the comprehensive operation relations of the truck assembly line are shown in Figure 17.

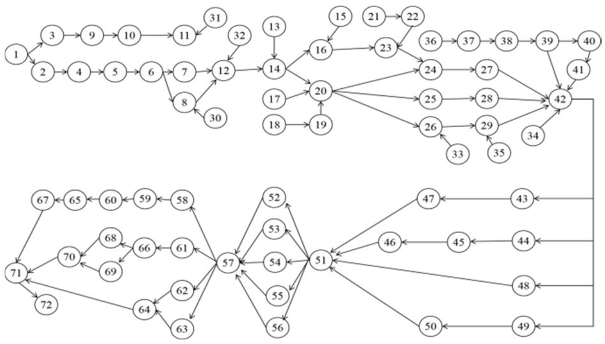

Fig. 17 Three types of trucks integrated operation task priority diagram

The worker cost required by the worker d in processing different tasks is shown in Table 14.

Tab 14. The worker cost of operating workers to process different tasks(Unit: yuan)

Worker d	worker cost of each operation task																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	25	6	19	24	30	35	32	48	27	49	52	39	25	81	32	90	47	36
2	11	14	51	57	39	74	71	44	23	26	62	38	19	18	50	92	42	53
3	7	14	18	21	29	36	24	28	42	51	32	26	18	35	28	29	34	51
4	6	41	58	32	63	26	38	39	41	51	29	49	58	14	25	36	18	28
5	8	65	30	62	39	23	46	68	25	61	28	54	19	29	32	45	19	34
6	15	15	35	62	54	58	25	63	21	45	34	25	36	28	31	45	15	19
7	12	36	25	64	52	45	28	65	18	35	15	64	63	65	15	25	15	6
8	22	9	13	18	24	93	49	80	95	65	18	72	54	54	19	35	67	19
9	26	21	32	15	65	19	28	36	25	45	59	32	21	28	65	24	45	12
10	34	29	65	25	24	23	18	12	65	54	25	45	44	46	40	25	39	14
11	18	35	29	15	29	32	29	29	22	39	65	29	18	81	25	38	29	25
12	16	46	23	19	69	29	37	35	65	28	69	89	25	73	51	21	38	99
13	21	51	29	63	64	52	25	65	59	51	32	58	45	26	15	29	14	81
14	38	29	26	32	15	9	18	25	36	54	56	25	49	43	39	35	18	97
15	42	53	21	29	23	28	35	25	18	69	84	39	25	58	99	82	57	36
16	53	43	31	64	58	29	44	25	36	56	67	91	44	61	44	58	24	25
17	27	56	25	37	84	34	25	35	91	83	85	35	43	45	88	25	55	45
18	25	51	62	24	33	52	18	62	81	36	29	85	49	69	24	33	38	82
19	8	17	15	58	35	72	29	80	56	66	28	9	28	78	72	34	15	36
20	14	16	25	66	71	36	64	65	45	25	15	18	24	68	35	44	49	56
21	17	45	13	45	20	18	35	61	44	62	28	18	28	18	65	82	32	21
22	35	21	27	69	52	36	36	12	18	95	78	30	51	98	66	24	13	76
23	46	15	65	59	29	34	33	65	75	25	7	53	66	36	6	21	28	26
24	30	16	55	54	29	30	64	28	32	11	40	44	15	29	38	25	65	38
25	29	32	29	63	37	18	44	29	38	65	18	26	28	28	19	17	34	42
26	34	12	22	29	17	49	64	55	32	65	34	28	29	55	29	64	38	61

Before optimization, optimized assignments and distribution of workers in each workplace of the mixed-model truck assembly line is shown in Table 15. Optimized assignments and distribution of workers in each work place of the optimized mixed-model truck assembly line is shown in Table 16.

Tab 15. The arrangement and allocation of tasks and workers at each workplace of the truck assembly line before optimization

Workplace	Task	A-type truck	B-type truck	C-type truck	Worker
1	1，2，17	261	273	266	18
2	3，4，5，6	204	236	203	15
3	7，8，13	265	265	270	5
4	15，21，31	233	236	226	19
5	34，61	190	190	200	7
6	9	180	190	186	21
7	10，11，12	260	260	245	11
8	14	310	310	310	22
9	16，18，40	260	264	265	15
10	19，20，22	250	250	280	24
11	23，24，25，30	308	305	230	5
12	26，27，28，29，32，33，36	202	210	315	21
13	35，37	305	305	302	25
14	38，39，41	210	210	180	18
15	42，43	280	280	260	10
16	44，45，46	305	305	280	23
17	47，48，49，50	245	248	294	26
18	51，52	332	332	332	16
19	53，54	305	305	300	2
20	56，55	310	310	310	20
21	57	320	320	320	1
22	58，59，66	280	276	289	6
23	62	278	278	278	17
24	60，68，69	320	320	316	10
25	63，65，70	305	305	250	4
26	64，67，71，72	300	300	315	9

Tab 16. The arrangement and allocation of tasks and workers at each workplace of the truck assembly line after optimization

Workplace	Task	A-type truck	B-type truck	C-type truck	Worker
1	1，13，21	295	305	290	11
2	2，17，30，40	306	308	311	8
3	15，35	307	310	302	16
4	3，4，18，22，41	298	300	302	12
5	5，6，9，32，33，36	295	298	329	15
6	8，37	310	310	310	13
7	10，11，19，31	291	291	296	19
8	7，12，34，38，39	305	305	295	8
9	14	310	310	310	14
10	16，20	310	314	315	18
11	23，24，25，26，28	300	297	304	13
12	27，29，42	308	316	302	6
13	44，45，48	305	308	306	16
14	43，47，46，49，50	305	305	322	16
15	51，52	332	332	332	13
16	53，54	305	305	300	5
17	55，56	310	310	310	15
18	57	320	320	320	2
19	58，62	313	314	317	8
20	59，61，66	295	290	300	13
21	60，68，69	320	320	316	7
22	63，65，70	305	305	250	46
23	64，67，71，72	300	300	315	8

By analyzing the data of mixed-model assembly line of the trucks before and after optimization, Table 17 is summarized. As can be seen from Table 17, the number of workplaces in the assembly line is reduced from 26 to 23, and the workload is reduced from 15.36 to 11.27. The workload among workplaces becomes more balanced, and the worker operation cost is reduced from 7,138 yuan to 6,257 yuan, saving worker costs.

Tab 17. Comparative analysis of indexes before and after optimization

Index	Before optimization	After optimization	Quantity of change
Production rhythm	332	332	0
Workload	15.36	11.27	4.09
Operating cost	7138	6257	881
Number of workplaces	26	23	3
Balance rate	86.35%	93.27%	6.92%

CONCLUSION

The study examines challenges related to workload imbalance in a truck manufacturer's mixed-model assembly line, resulting in the following key findings:

(1) A mathematical model has been established with multiple objectives, including minimizing the number of workplaces, actual production rhythm, and assembly costs on the mixed-model assembly line. This model also aims to achieve a balance of workload among the workplaces, ensuring efficient operation across the entire line.

(2)The main improvements have been made to the encoding operations of the genetic algorithm, the generation of the initial population, and the selection of crossover and mutation operations to construct the fitness function. And an adaptive crossover and mutation probability has been proposed. Selecting examples from literature to test the performance of the improved genetic algorithm. The optimal solution is obtained through Matlab programming. The results show that the workload between the assembly line workplaces has decreased from 0.653 to 0.513, the labor cost has been reduced from 1872 yuan to 1786 yuan. And the running time has been decreased from 43 seconds to 27.3 seconds. Using Flexsim simulation software, an improved mixed-model assembly line simulation model was established, and the corresponding parameters were set. The running results indicate that after the improvement, the utilization disparity among the workplaces of the mixed-model assembly line has decreased compared to before the improvement. This has led to more stable overall utilization of the workplaces. Furthermore, the results show that a balance of workload among the workplaces has been achieved, contributing to the enhanced efficiency of the entire assembly line.

(3) Balancing optimization of a truck assembly line for a certain automobile company. The results indicate that the number of workplaces in the assembly line has been reduced from 26 to 23, and the workload has decreased from 15.36 to 11.27. The workload among the workplaces has become more balanced, and the worker cost has been reduced from 7,138 yuan to 6,257 yuan, achieving labor cost savings. The optimization objectives and the enhanced genetic algorithm, have proven to be effective for addressing the multi-objective balance optimization challenges of the truck mixed-model assembly line.These improvements have been specifically tailored for a certain automobile company, demonstrating their practical applicability and success in optimizing the assembly line processes.

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NOMENCLATURE

I the total number of product assembly tasks

i the number of product assembly tasks $i = 1, 2, 3, \ldots, I$

K the total number of products

k the product number $k=1,2,3,\ldots,K$

M the total demand of all products in the planning period

M_k the required quantity of the product with number k

q_k the demand ratio of the product numbered

CT_{theory} the theoretical production rhythm

CT the actual production rhythm of the assembly line

N the total number of workplaces

n the number of workplaces $n=1,2,3,\ldots,N$

T_{ki} the product with product number k, and its working time when assembling the task with number i

T_{kn} the product with the product number k, indicating its total operation time at the workplace with the work number n

T_n the total time required for the product to be assembled at the workplace with the work number n

D the total of the number of workers to be equipped on the assembly line

d the worker number $d = 1, 2, 3, \ldots, D$

C_{di} the assembly cost of the worker d processing the task i