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Simulated Annealing Algorithm and Implementation Software for Fabric Cutting Problem

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ABSTRACT

The development of loom technology has significantly increased the efficiency of fabric output in the textile industry. Additionally, preventing the occurrence of defects during the manufacturing process on the fabric is not easy. Therefore, after the production is completed, the aim is deciding the cutting location of the product, which has the defect map, to increase the first quality product quantity by considering the customer quality parameters. In this article, a decision support system has been developed to help the inspector in the final stage which will also prevent losses. The utilized algorithm is the Simulated Annealing algorithm, which is well known and rendered good results for different types of problems in the literature. In the study, a sample problem is used to explain the adaptation of the algorithm to the problem, and the design of the experiments is deployed to obtain the best parameter values for the algorithm. Finally, the software, which is prepared to use the algorithm in the real production environment, is introduced and the results of the performance analysis are evaluated. The results demonstrated that the developed software is capable of making high ratio first quality fabric decisions within seconds.

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Cutting algorithm, simulated annealing, software

1. INTRODUCTION

Since textile is one of the most important actors in the fashion area, the manufacturers must be leading companies in such matters as production technology, delivery times, and quality levels to adapt to the ever-changing customer behaviors. In the last stage of the weaving industry, it is critical to decide the cutting locations of fabric, considering customer quality requirements, to boost firm profitability. Note that the prerequisite for conducting this study is registering the types and locations of defects on fabric into the database. In this study, defect detection is done by manual inspection. Then the collected data is transferred to the system database to obtain the defect map. The principal objective is to increase the resulting first quality fabric length. Those in the industry know that the profit loss from the first to the second quality is incredibly high. The focus of this study is to develop a decision support system that can solve this problem in seconds.

As the first attempt in the solution stage of the mentioned real production environment problem, a procedure was developed which splits the fabric in larger lengths into smaller subsections. The method proceeds considering the quality parameters of the customer company. The next step is to attain the highest quantity of first quality fabric from sub-parts obtained by the procedure. In order to solve the mentioned problem, Simulated Annealing (SA) metaheuristic is adapted to the cutting fabric problem in this paper.

SA algorithm is one of the well-known heuristic techniques based on the steps in the annealing process, which aims to ensure that the crystal structure is regular in the heat treatment of metals. Acceptance of bad solutions with some probability prevents convergence to local optimum points. As will be mentioned in the literature review, SA was applied to various problems, and good results were obtained. In the next step, SA's parameter values will be optimized, user interfaces will be developed, and performance evaluations will be made.

The main contributions of this research are evaluated regarding the methodology adopted and the application area. The first contribution is the recommended procedure

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for splitting the large woven parts into sub-parts to meet customer conformity. The second contribution is the application of the SA algorithm in a real production plant, which solves the real production area problems with high first quality ranges and in seconds.

This paper is organized as follows: Section 2 provides a literature review of cutting problems, which has a similar structure with the problem at hand. The problem description is made in Section 3. SA is presented in Section 4. Computational results are displayed in Section 5. The paper is finalized with the conclusion and future research directions in Section 6.

2. LITERATURE REVIEW

Despite the NP-hard structure of cutting problems (Brandao and Pedroso [1]), researchers usually develop heuristic methods. The main idea is, cutting the large objects into smaller items to meet customer demand. Optimization of these kind problems generally provides high economic savings. Cutting stock problems have been encountered in many production processes as wood, steel, meat, paper, and also in logistics applications such as cargo loading.

A literature review by Haessler and Sweeney [2] discusses the basic formulation and solution procedures for one- and two-dimensional cutting problems. In the study of Wäscher et al. [3], the cutting and packaging algorithms were grouped by considering the problem types and sizes (1, 2, 3 dimensional). The special cases of problems often involve not being able to include a specific group and can be grouped in the "other" class. The work in our paper, as will be elaborated later, will be referred to in the other group in the future, because of carrying many specific features. Some of the two-dimensional problems and their solutions in the literature are Rodrigo et al. [4], Fathy et al. [5], Andrade et al. [6], Cui and Zhao [7], Kim et al. [8], Afsharian et al. [9]. Javanshir et al. [10] focused on the field of readymade of the textile sector. The planning of cutting was to minimize total fabric consumption, which was compatible with the two-dimensional cutting problem, and the simulated annealing algorithm was used for the solution in their study.

Some studies in the literature related to the cutting problem can be compiled as follows.

In the study by Poltroniere [11], the cutting problem is studied in scheduling problems, and also machine setup time and scrap costs were considered simultaneously in the case. Heuristic methods were developed for the problem, and the calculation results were discussed. Arbib and Marinelli [12] developed an integer linear programming model and heuristic methods in another study where cutting operations were scheduled by taking into consideration the product delivery dates. In the paper of Araujo et al. [13], minimization of the number of parts and the number of different cutting patterns were considered, which are two objective functions that are contradictory to each other. A genetic algorithm was developed for the mentioned problem and tested on randomly generated and real data set. Another hybrid heuristic that minimizes the number of different cut shapes was also developed by Yanasse and Limeira [14]. In another study by Lai and Chan [15], the simulated annealing algorithm with artificial intelligence was developed for the cutting problem, and the algorithm was tested with random generated and real datasets. Another method that provides good and fast results for situations where there are a large number of pieces to cut was developed by Brandao and Pedroso [16].

The issue to be addressed in this paper is the one-dimensional cutting problem. Although the number of dimensions decreases, the constraints arising from the problem structure increase complexity. In the study of Afsharian et al. [9], these problem variants are called as "more specialized, less standardized" because of considering large defective objects. For the glass cutting problem, which can be classified in this category, the researchers developed a dynamic programming algorithm [17], mixed integer programming based algorithm [18], and genetic algorithm based solution [19]. The paper of Rönnqvist [20] provided an overview of wood flow in the forestry industry and some optimization models, including cutting problems. The problems in glass cutting, forest, steel, or textile industry might seem similar, but defect types, quality classes, different customers' diverse requirements, make each problem type unique actually. In the study of Cherri et al. [21], an extensive literature review was made on the one-dimensional cutting stock problem that takes into account the usable leftovers, if large enough, to meet future demands. The study of Poldi and Arenales [22] carried out in this context, the situation of the subsequent periods was also taken into consideration. The range of products in the textile sector is extensive, and the main customers' order variability decreases the possibility of re-using the product for future demands. So, the problem to be solved in this study also differs from the scope mentioned. The textile industry makes many problems special because of its natural structure. For example, again in the weaving sector, Eroğlu et al. [23] proposed a genetic algorithm for scheduling, which divided the jobs and assigned to machines simultaneously. The problem of cutting, which is encountered in the last stage of weaving and which will be discussed in this paper, has been studied rarely in the literature. The problem in the study, which was done by Özdamar [24], is compatible with the foundation stones of the problem in this paper. Özdamar [24] emphasizes the differences of the problem structure in her study, as summarized below.

Whitaker and Cammell [25] aimed to increase the total income by considering meat quantities in different sources besides meat cutting capacities. Meat is a function of variables such as meat, gender, amount of fat in the meat industry and includes causality. Sculli [26] discussed the effects of scratches on adhesive tape, and the total usable length to be divided into standard lengths became a random variable in the study. Sweeney [27] studied the trimming of multi-length strips of different quality classes in the master roll. In that study, the quality of the master roll to which small pieces were to be cut was predetermined. In all the studies in this paragraph, there are different quality classes and predetermined product lengths. However, in this study, a quality class will be obtained after cutting operation. So, to find the best cutting locations, so many criterions -e.g., as defect score, the number of the critical defect, maximum defect length, the size of the fabric itself- have to be considered as it will be discussed in the next sections.

Fabric defects are responsible for approximately 85% of defects in the garment industry [28]. This study tries to maximize the first quality product, which includes different kinds of defects. So, as a first step, the required information about defects (e.g., type, quantity, length, location) has to be collected to obtain the defect map. Although this defect map has already been available in this study, please note that there is extensive literature research on this context. Ngan et al. [29] studied on literature review on automated fabric defect detection methods proposed in recent years. These methods are mainly grouped by utilized methods as the spectral approach, model-based approach, learning approach (neural networks), and structural approach. The researchers also analyzed the strengths and weaknesses of these approaches. Mahajan et al. [30] also studied on review of fabric defect detection methodologies. In the study, defect detection methods are grouped into statistical, spectral, and model-based approaches.

Although the study in this paper is coincident with the problem structure defined by Özdamar [24], the model has to meet all the needs of the dynamic production environment. For this reason, the quality parameters of different customers must be carried out under the real system. Additionally, big parts' splitting procedure is developed, which runs primarily.

3. PROBLEM DESCRIPTION

Due to the lack of more recent work on this special topic, the problem instance in the study of Özdamar [24], is taken into consideration in this section to provide the integrity and show differences of this paper. In the problem, Figure 1a shows the piece of fabric that contains defects with different types and lengths. In our work, the new dimension added to the problem is due to the natural structure of the real problem. Table 1 shows that; the quality definitions of different customers are diverse. When the fabric in Figure 1a was cut in two places, as demonstrated in Figure 1b, quality levels of obtained fabric parts vary by customer. Evaluating these two parts, according to Customer A's criterion in Table 1, the first part defect score can be calculated using Formula (1). According to these computations, the first fabric part in Figure 1a can be graded as first quality according to the first criteria of Customer A's requirements. Similarly, the second part of the fabric can be graded as second quality according to the first criteria of Customer A's request. This calculation is demonstrated in Formula (2). However, the product must be able to meet all the criteria in Table 1 to get the quality grade.

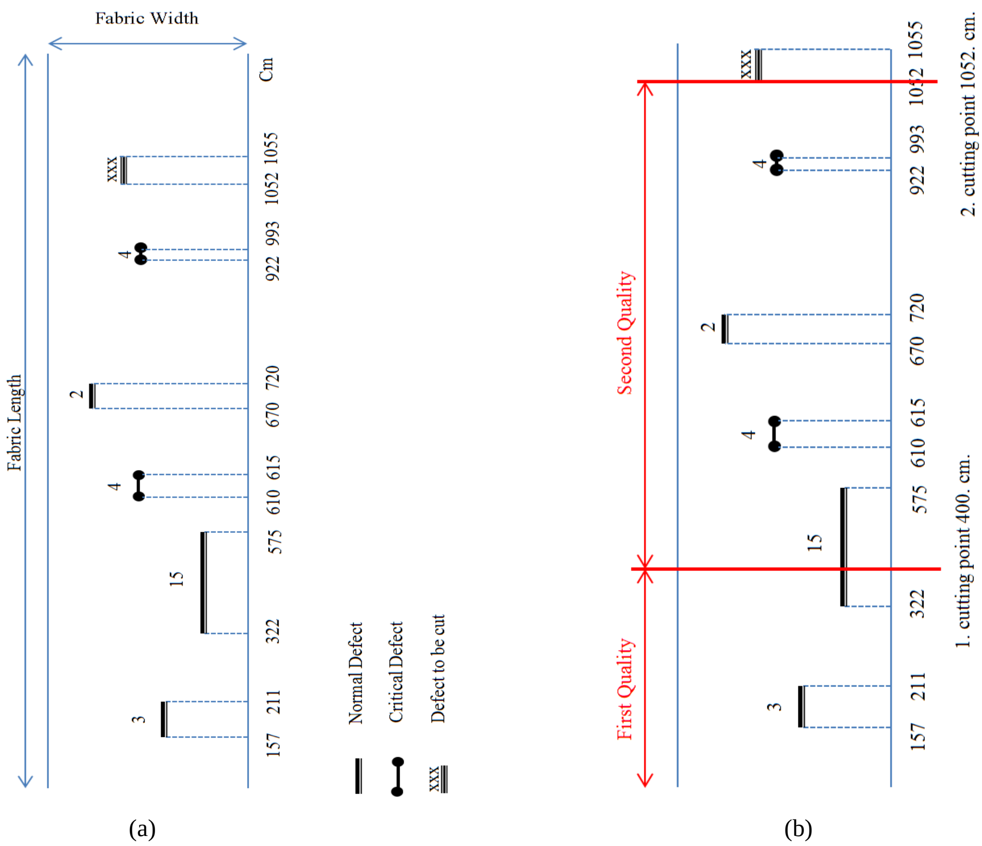


Figure 1 a. Piece of fabric with different types and length of defects **b.** Cutting points of fabric

Table 1. Different quality expectations of different customers

Criterion in a roll of fabric \ Quality Level	Customer A			Customer B		
	1	2	3	1	2	3
Defect score for each part	20	160	320	-	-	-
Critical defect quantity in 100 meter (m)	5	15	30	3	15	40
Maximum defect length (m)	3	300	300	1	300	300
Maximum part quantity	3	5	7	3	5	7
Minimum part length (m)	18	10	3	15	10	3
Maximum roll length (m)	300	300	70	150	300	300
Distance between two critical defects	5	0	0	3	0	0

First part defect score: $3+\frac{(400-322)}{(575-322)}*15 = 7.62$ (1)

Second part defect score: $\frac{(575-401)}{(575-322)}*15+4+2+4=20.33$ (2)

The contributions of the study in this article can be summarized as follows;

The real problem involves different quality expectations of different customers, and the solution must be able to respond to this demand. To solve the problem in the real production environment in seconds;

1. A procedure that splits large parts into smaller sub-parts is proposed;
2. SA algorithm is adapted to the more complex real problem;
3. The software is developed to respond to real production requirements.

The steps of the SA algorithm and the evaluation results are detailed in the next sections.

4. UTILIZATION OF THE SIMULATED ANNEALING ALGORITHM

One of the most critical points of the problem is meeting the customer demand both on quantity and quality basis. The aim is to increase the quantity of first quality fabric length by cutting the part from the detected points. The important point is to obtain the fabric that is compatible with the customer requirements. The solution to the problem is designed considering the following constraints. Note that these constraints are customer-specific, as indicated before.

- ✓ Defect score in 100 m^2 (area)
- ✓ The number of “main” defects in 100 meter (m)
- ✓ Maximum defect length
- ✓ Minimum length (m) between two defects
- ✓ Defect score in 100 m (length)
- ✓ The number of defects in 100 m
- ✓ Minimum part length (m) in a roll
- ✓ Maximum roll length (m)
- ✓ Minimum roll length (m)
- ✓ Clear zone in starting and ending of the fabric
- ✓ Non-defective zone in starting and ending of the fabric

4.1 Determining real sections

This stage emerged from the quality requirements of customers. In order to meet customer demands (maximum and minimum roll length), the fabric is needed to be split into subsections (real sections). The following example might be reviewed to explain the procedure; If we have 362 meter (m) fabrics, and we have constraints of “Maximum Roll Length” and “Minimum Part Length” for Customer B, as in Table 1, to find the minimum and the maximum number of actual sections, the following calculations are needed to be done. Please note, for Customer B, “Minimum Roll Length” is equal to “Minimum Part Length.”

- ✓ Minimum Number of Section = Round-Up (Fabric Length / Maximum Roll Length) = Round-Up (362 / 150) =3
- ✓ Maximum Number of Section = Round Down (Fabric Length / Minimum Roll Length) = Round Down (362 /15) =25

Then, the algorithm finds the feasible solution by;

- ✓ Decreasing one by one from the maximum number of section to the minimum number of section,
- ✓ Making 10 000 trials in each stage,
- ✓ A feasible solution that provides constraints is found. Section quantity must be between the minimum and the maximum number of sections.

In this example, the number of real sections might be between 3 and 25, as calculated. There is not any restriction caused by loom in real sections for the studied factory. Consider Figure 2a, assume that the initial solution cuts the fabric into three real sections. Dashed lines in Figure 2 shows generated virtual cutting points. SA will be applied to each of sub-parts to generate these virtual points. Details of algorithms will be analyzed in the next subsections. Algorithms can be run as much as desired (parametric) for each real section. Figure 2a, Figure 2b and Figure 2c demonstrates different runs of an algorithm for a problem.

The first quality length of the fabric is determinative for selecting the best solution. After processing three runs, the section, which gives maximum first quality fabric length, can be chosen. Selected parts for the examined example are shown by ellipses in Figure 2.

4.2 Simulated Annealing Algorithm

Simulated annealing (SA) is a well-known metaheuristic that is developed by Kirkpatrick et al. [31] in the early 1980s. The working mechanism of the algorithm can be described as following: In the heat treatment of metals, all the molecules adjust themselves to the liquid phase by heating the metals to the melting point. If the cooling is done properly, the crystal structure becomes regular. In the SA, it is decided to go to which decision team while reducing the temperature continuously. It is a local progress method that works with the probability structure. Simulated annealing occasionally accepts worse solutions. This characteristic of simulated annealing helps it to jump out of any local optimums and converge to the global optimum point. The general steps of the algorithm can be summarized as follows;

Step 0: Set parameter values

- ✓ Initial Temperature: T_0
- ✓ Markov chain length (Number of iterations at the same temperature): L (ℓ is a counter for Markov chain length)
- ✓ Cooling rate: C (Recommended between 0.5-0.99)
- ✓ Number of iteration: k (The other criteria might be stopping temperature)
- ✓ Maximum number of iteration: K

Step 1: Create an initial solution

- ✓ $x^* = x^0$
- ✓ $Z(x^*) = Z(x^0)$
- ✓ $\ell=0$, k=0

Step 2: Create a neighbor solution (x^1)

- ✓ Calculate $\Delta Z=Z(x^1)-Z(x^*)$
- ✓ We wish $\Delta Z<0$ in minimization problem (in maximization problem $\Delta Z>0$)

Process Step 3 or Step 4

If $\Delta Z<0$ (if the objective is minimization) (in maximization problem $\Delta Z>0$)

Step 3: Make the following assignments

- ✓ $x^*=x^1$
- ✓ $Z(x^*) = Z(x^1)$
- ✓ $\ell=\ell+1$, k=k+1

Else

Step 4: Move on a bad solution with a probability of "r" (r is a random number between 0-1)

If $e^{-\Delta Z/T}>r$ (in maximization problem $e^{\Delta Z/T}>r$)

- ✓ $x^*=x^1$
- ✓ $Z(x^*) = Z(x^1)$
- ✓ $\ell=\ell+1$, k=k+1

Else, continue from the previous solution

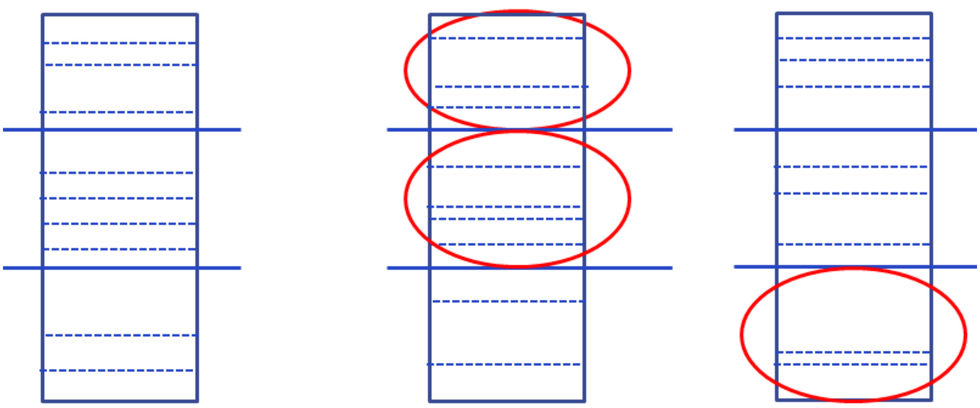
Step 5: If l = L make the following assignments;

- ✓ T=C*T
- ✓ $\ell=0$
- ✓ If k=K then stop

Else, go to Step 2

SA has been used as a very effective tool for solving many different types of problems ([15], [24]). Note that, defining initial and neighbor solutions are specific to the problem. For the different types of problems, T, C, L, and stopping criteria are algorithm-specific. There are different cooling strategies as stepwise or continuous temperature reduction.

The problem is adapted to the determination of cutting location in the weaving industry. Consider the example in subsection 4.1 and Figure 2; Start from any of the selected virtual cutting point (initial solution). Check objective function value and quality constraints. If necessary, according to the algorithm, merge the virtual cutting point with the next one (moving direction selection is made randomly). That is the neighborhood generation phase of SA. In subsection 5.1, a numerical example will be demonstrated to explain the methodology.



(a) (b) (c)

Figure 2. Three different runs of SA

5. COMPUTATIONAL RESULTS

5.1 Numerical Example

Consider the following example to explain the general concept of the problem. The proposed model splits fabric, which is 1 717 m in total length, into 14 real sections according to the procedure that was defined in Section 4.1. Each section's starting and ending points are shown in Table 2. The next step is applying SA to each of these sections.

Table 3 shows the defects of the first real section in Table 2. That defect map will be used to decide cutting points. The SA will be tried out to define cutting points. Please note, if the defect is in length, Score value, which is in the last column of Table 3, can be calculated as in Formulation (3);

$$\text{Score} = \text{Defect Score} * \text{Lenght of Defect} \quad (3)$$

Otherwise, if the defect is a point, Score is equal to Defect Score as stated in Formula (4);

$$\text{Score} = \text{Defect Score} \quad (4)$$

The SA will start the iterations from virtual cutting points. For example, the initial solution might be cutting the fabric virtually from 12nd, 59th, 105th, 200th meters. Then the SA iterations proceed. The algorithm will start iterations by merging the virtual subparts in the same quality level. If the virtual part is in the first quality, move backward or forward to get the bigger first quality part. However, consider all quality requirements of a customer while doing these operations. The backward or forward progress step is considered as 1cm. The first quality virtual cutting points of the first real section are shown in Table 4. According to the optimal solution in Table 4, the fabric has to be cut from 108.445th meter to get first quality fabric parts. Additionally, there must be some cut-offs from the end of the fabric to achieve customer quality requirements.

Table 2. Real sections of the total fabric

Real Section Nr.	Section Starting Point (m)	Section Ending Point (m)	Length of section
1	0.01	212.01	212.00
2	212.02	594.16	382.14
3	594.17	594.37	0.20
4	594.38	756.06	161.68
5	756.07	760.38	4.31
6	760.39	881.92	121.53
7	881.93	882.54	0.61
8	882.55	1031.1	148.55
9	1 031.11	1 034.42	3.31
10	1 034.43	1 039.97	5.54
11	1 039.98	1 043.35	3.37
12	1 043.36	1 489.07	445.71
13	1 489.08	1 490.23	1.15
14	1 490.24	1 716.99	226.75

Table 3. Defects of the first real section in Table 2

Defect ID	Defect Starting Point (m)	Defect Ending Point (m)	Length Between two defects	Length of defect	Score
0	0.01	5.35	7.22	5.34	38.02
1	12.57	12.57	2.27	0	1
2	14.84	14.84	2.25	0	1
3	17.09	17.09	2.08	0	2
4	19.17	19.17	4.65	0	1
5	21.3	23.82	4.04	2.52	10.08
6	27.86	27.86	1.49	0	1
7	29.35	29.35	4.48	0	1
8	33.83	33.83	1.34	0	1
9	35.17	35.17	14.33	0	1
10	49.5	49.5	6.71	0	2
11	56.21	56.21	6.74	0	1
12	62.95	62.95	21.72	0	1
13	84.67	84.67	2.69	0	2
14	87.36	87.36	4.7	0	1
15	92.06	92.06	6.09	0	2
16	98.15	98.15	13.1	0	2
17	111.25	111.25	3.19	0	1
18	114.44	114.44	4.85	0	1
19	119.29	119.29	2.11	0	4
20	121.4	121.4	7.95	0	1
21	129.35	129.35	13.62	0	1
22	142.97	142.97	4.42	0	1
23	147.39	147.39	2.76	0	1
24	150.15	150.15	6.71	0	3
25	156.86	156.86	9.66	0	1
26	166.52	166.52	8.02	0	3
27	174.54	174.54	6.48	0	1
28	181.02	181.02	2.71	0	1
29	183.73	183.73	15.57	0	1
30	199.3	199.3	3.41	0	3
31	202.71	202.71	4.65	0	2
32	207.36	207.36	2.97	0	1
33	210.33	210.33	1.68	0	1
34	211.54	212.01		0.47	1.88

Table 4. The best solution of SA for the first real section

Row Nr.	Quality	Starting Point of Cut (m)	Ending Point of Cut (m)	Length of Fabric
1	**0**	**0.010**	**5.350**	**5.340**
2	1	5.360	108.445	103.085
3	1	108.445	211.530	103.085
4	**0**	**211.540**	**212.010**	**0.470**

5.2. Design of Experiment (DoE) for parameter selection of SA

The main parameters and levels of parameters that affect the performance of the software are determined, as presented in Table 5.

Table 5. Experimented parameter values of the SA

Parameters	**Levels**
Markov chain length: L	1 000 ; 5 000 ; 8 000 ; 10 000
Stopping Temperature: T	0.6; 0.7
Cooling Rate: C	0.8; 0.97

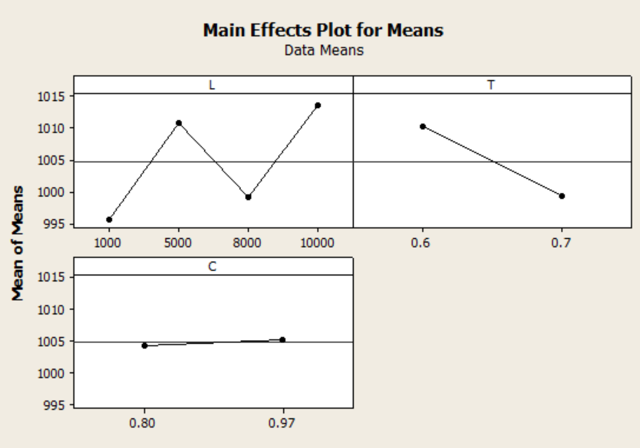


Figure 3. Main effects plot of the three factors

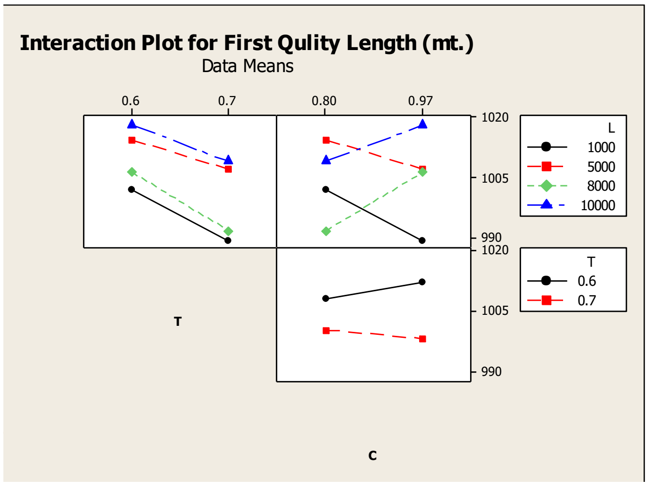


Figure 4. Interaction plot of L, T, and C

The experimental design that fits these levels is Taguchi L8 (4**12 **2). Minitab 16 is used for experimental design. The objective is to increase the first quality fabric length. According to the main effects plot in Figure 3, when L is equal to 10 000, T is equal to 0.6, C is equal to 0.97, SA yields the best performance regarding first quality length. According to the interaction plot in Figure 4, there is a significant interaction between parameters L and C. Figure 4 also indicates that the selected parameter value for L and C would be 10 000 and 0.97, respectively.

5.3. Performance of SA

The user interface of the algorithm can be seen in Figure 5. In application, it is easy to select customer quality requirements and the number of trials. The result section selects the best solution for each real section, as mentioned before. The values of SA parameters are parametric in the designed interface to present user-friendly and flexible software.

Table 6 summarizes the performance of SA. Because of quality constraints, data in Table 6 belong to the same customer. Each part (instance) has a length, total defect score, and total defect quantity, as shown in Table 6. The number of the trial (run) in SA is selected as 10 for each instance. All data in Table 6 has the following structure;

- ✓ Order lengths of instances are between 1 000 and 1 600 m.
- ✓ The total defect score of instances is between 100 and 300.

After running SA, discarded length for each instance can be found automatically. Then, first quality length, first quality percentage values in Table 6 can be calculated easily. The elapsed time of SA can be seen in the last column of Table 6. These values are in second, and elapsed time value is the summation of 10 runs duration. This computation performance is the most important feature of the utilized algorithm. Because of that, SA is developed to be a tool of optimization in the real production plant. Moreover, it has been already in use in many weaving factories as the decision support system that assists senior workers in cutting the fabric from the optimum location. Increasing the first quality fabric quantity will directly affect the total income of the factory.

The main purpose of the algorithm is to maximize the first quality product quantity considering the requirements of customers. Sometimes one defect may render the product unusable. That is why it is better to use defect score instead of the number of defects for comparisons. The defect score might be minimized by cutting schema. So, the best way to increase the first quality percentage is by cutting the fabric from the best place to decrease the defect score. The total defect score is divided by the length of fabric to reach a scaled defect score for each instance, as it is shown in Table 6. In order to show the relationship between the scaled defect score and the first quality percentage of each instance, the correlation analysis has been done by Minitab 16. According to results, the Pearson correlation coefficient between the scaled defect score and the first quality percentage is -0.569, which represents a negative relationship between the parameters. As scaled defect score increases, the first quality percentage decreases. The p-value is 0.004, which is less than the significance level of 0.05. The p-value indicates that the correlation is significant.

Table 6. Performance of the SA

Part ID	Length of Fabric (m)	Total Defect Score	Total Defect Quantity	First Quality Length (m)	Scaled Defect Score (Round-up)	First Quality Percentage (Round-up)	Elapsed Time (sec.)
1	1 415	300	170	1 145.18	0.22	81%	44.66
2	1 233	188	101	942.23	0.16	77%	33.21
3	1 382	190	114	1 208.08	0.14	88%	26.68
4	1 556	194	92	1 464.85	0.13	95%	22.25
5	1 122	201	61	1 018.43	0.18	91%	35.33
6	1 582	104	50	1 546.66	0.07	98%	4.28
7	1 093	186	52	1 012.25	0.18	93%	20.78
8	1 293	103	41	1 269.93	0.08	99%	4.34
9	1 566	123	52	1 545.25	0.08	99%	3.95
10	1 407	174	102	1 387.61	0.13	99%	4.62
11	1 308	182	68	1 208.13	0.14	93%	9.17
12	1 102	136	97	1 048.67	0.13	96%	7.63
13	1 201	151	103	1 154.15	0.13	97%	20.44
14	1 201	156	67	1 042.58	0.13	87%	12.39
15	1 208	147	80	1 186.04	0.13	99%	5.55
16	1 202	145	52	1 178.88	0.13	99%	6.66
17	1 152	147	51	953.64	0.13	83%	54.11
18	1 084	100	74	1 047.25	0.1	97%	8.19
19	1 101	179	132	1 057.11	0.17	97%	135.38
20	1 327	188	83	1 231.59	0.15	93%	26.39
21	1 034	184	105	904.86	0.18	88%	13.13
22	1 045	166	84	940.7	0.16	91%	6.34
23	1 195	176	69	1 132.93	0.15	95%	9.58
24	1 202	184	77	1 117.81	0.16	93%	2.83

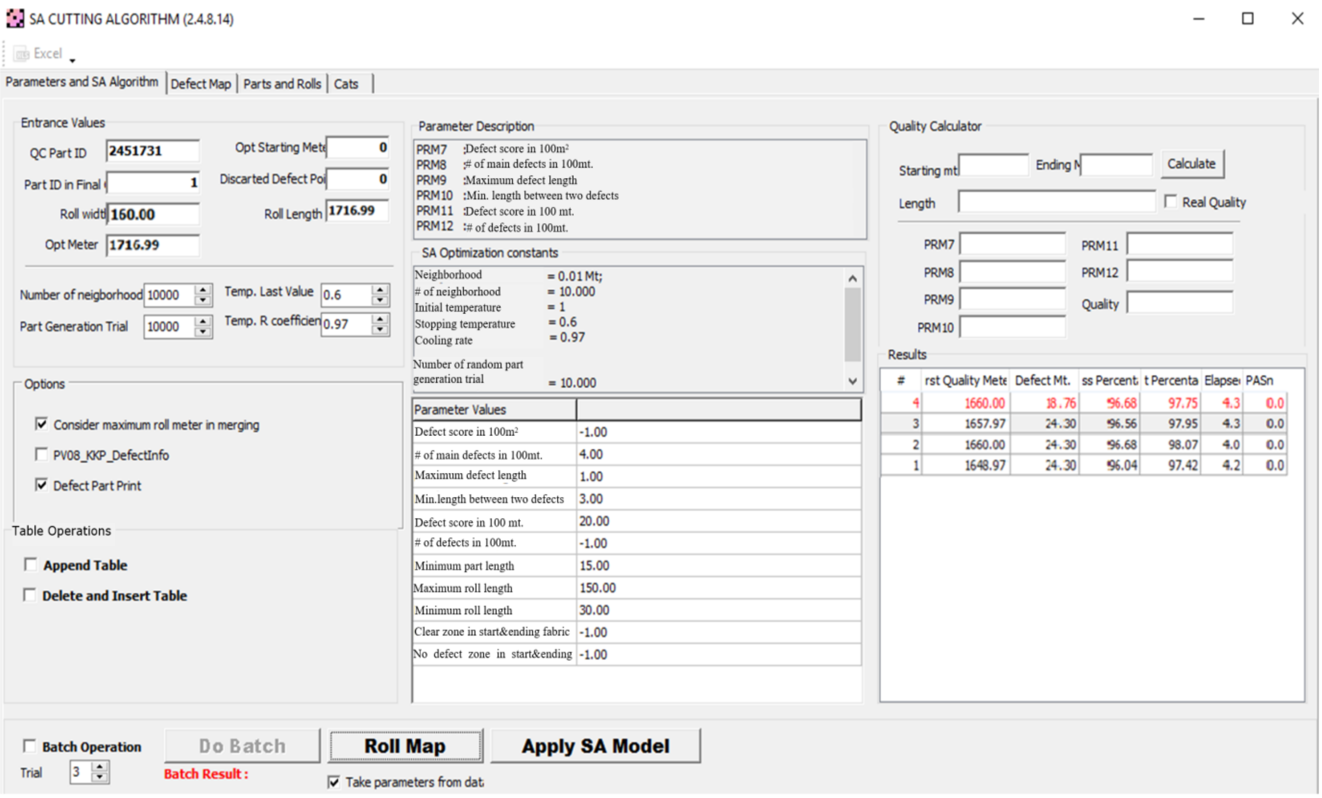


Figure 5. User interface of SA Application

6. CONCLUSIONS AND FUTURE DIRECTIONS FOR RESEARCH

In this paper, the Simulated Annealing algorithm is adopted to decide cutting points of large lengths of fabric in the weaving industry. All constraints of real production plant are included in the problem. First, to work on certain sized parts, which consider customers' requirements, the fabric is cut into real sections by following the steps of the proposed procedure. Second, after describing the methodology of SA, DoE is utilized to get better performance parameters. In the last phase, the user interface of SA is introduced, and the performance of the algorithm is analyzed. According to the achieved results, the SA can be used as the decision support system of the fabric cutting phase in the real production plant in the sense of both high first quality percentage rates and calculation time performance in seconds.

During the project, while progressing on SA, on the other side, the K-means algorithm was studied to find defect intensive regions and cut these regions off the part. SA performed better results than K-means for some tryouts. However, much more comparative analysis in terms of statistical evaluations and tests are required. So, as a future study, SA and K-means algorithms might be compared with different parameters. Another future research direction might be utilizing K-Means algorithm as an initial solution of SA. Mixed Integer Programming (MIP), which would include all requirements of different customers, might be developed to be used in the real production plant. Additionally, other well-known meta-heuristic techniques might be applied to the problem.

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