

A Greedy Randomized Adaptive Search for Solving Chance-Constrained U-Shaped Assembly Line Balancing Problem

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ABSTRACT

This paper discusses the U-shaped assembly line balancing problem in case of stochastic processing time. The problem is formulated using chance-constrained programming, and the greedy randomized adaptive search procedure is used to solve the problem. In order to prove the efficiency of the proposed algorithm, 71 problems taken from well-known benchmarks are solved and compared with the theoretical lower bound, and 13 of them were compared with another approach used to solve the same problem in another paper, which is beam search. The results show that 59 problems are the same as the theoretical aspiration lower bound. In addition, the results of 11 of 13 problems compared with beam search are the same, and the results of two problems are better than beam search. The t-test statistics is applied and showed that there is no significance difference between the proposed algorithm and the theoretical lower bound; thus, the proposed algorithm shows efficiency when compared with the aspired values of the theoretical lower bound.

KEYWORDS

Chance-Constrained Programming, Greedy Randomized Adaptive Search Procedure, Local Search, Meta-Heuristics, Taguchi Method, U-Shaped Assembly Line Balancing Problem

1. INTRODUCTION

The assembly line is of great importance in industry. It simplifies the assembly processes of the products by implementing them in a set of stations instead of having all the work done by a single skilled worker. It reduces the learning aspects, and it guarantees a fixed time for completing the assembled products. The assembly line balancing problem (ALBP) is such a problem that seeks to optimize the assignment of the assembly tasks to achieve some objectives such as minimizing the number of stations or minimizing the cycle time. The simplified assumptions of the problem contain three constraints. The first one is to assign each task in only one station. The second one is to ensure that each station time does not exceed the cycle time. The third one is to confirm that each task is

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assigned after its predecessors. The U-shaped assembly line balancing problem is one of the assembly line balancing problems that have one of the practical relevance, which is the U-shaped line. In this type of assembly lines, the precedence constraints are related to both of the predecessors and successors of the tasks, where any assembly task must be assigned after either its predecessors or its successors.

This paper discusses the U-shaped assembly line balancing problem in case that the processing times of the tasks are normally distributed random numbers with known means and variances. Therefore, the cycle time constraints herein are represented as chance-constraints that realized by minimum probabilities. In order to solve the problem, the chance-constraints are converted to non-linear deterministic constraints. The proposed algorithm for solving the problem is one of the single-solution based metaheuristics, which is greedy randomized adaptive search procedure (GRASP). In order to have the best results of the proposed algorithm, its parameters are optimized using Taguchi method. The computational results are constructed by implementing the proposed algorithm on 48 adapted problems selected from well-known deterministic benchmarks found in <https://assembly-line-balancing.de/>. The adaptation is done by considering the processing times of the selected benchmark problems as the expected processing times of the tasks and the variances are calculated using the method of Carraway (1989). In such method, the variance for each task is to be generated

randomly from $\left[0, \left(\frac{\mu_i}{4}\right)^2\right]$ for low variances and from $\left[0, \left(\frac{\mu_i}{2}\right)^2\right]$ for high variances. The selected

problems of for computational results are solved in case that the chance probabilities are equal to 0.90, 0.95, and 0.975. To proof the efficiency of the proposed GRASP algorithm, the computational results is compared with the results of constrained programming approach found in (Pınarbaşı, 2021).

The paper is organized as follows: the second section presents a literature review of the U-shaped assembly line balancing problem. The third section shows the methodology used in the paper. The fourth section presents the proposed mathematical model for CUALBP-1. The fifth section proposes a GRASP approach to solve the problem. The sixth section produces an experimental design to optimize the parameter levels of the proposed algorithm. Eventually, the seventh section shows the computational results.

2. LITERATURE REVIEW

This section shows some information about the previous work in the U-shaped assembly line balancing problem. The problem was first presented by Miltenburg and Wijngaard (1994), where they developed a dynamic programming approach based on a heuristic to solve the problem. Ajenblit and Wainwright (1998) developed a genetic algorithm to minimize the number of stations. Nakade and Ohno (1999) solved the problem by using a heuristic approach. Their paper handled multi objectives, where they minimized the cycle time and the number of assigned workers. Erel et al. (2001) developed a simulated annealing approach to minimize the number of stations of the problem. Gökçen et al. (2005) solved the problem by using the shortest route approach, where they sought to minimize the number of stations. Gökçen and Ağpak (2006) used a multi-criteria decision-making approach for achieving several conflicting goals.

Baykasoğlu (2006) developed a simulated annealing approach to maximize the smoothness index and to minimize the number of stations. Kim et al. (2006) presented an endosymbiotic evolutionary algorithm to maximize workload smoothness. Hwang et al. (2008) developed a genetic algorithm to optimize multiple objectives, which are minimizing the number of stations and minimizing the variation of workload. Kara et al. (2009) produced a fuzzy goal programming for U-lines. Özcan and Toklu (2009) used Simulated annealing and genetic algorithm to maximize the line efficiency and to maximize the smoothness index. R. Hwang and Katayama (2009) developed an evolutionary algorithm to minimize the number of stations and the variation of workload. Bagher et al. (2011) used a hybrid evolutionary algorithm to solve the problem under uncertainty to minimize the number

of stations, total idle time, and non-completion probabilities of each station. Kazemi et al. (2011) developed a genetic algorithm to minimize the total costs associated with the number of stations and task duplication. Hamzadayi and Yildiz (2012) presented a genetic algorithm to minimize the number of stations and maximize the smoothness index. Rabbani et al. (2012) developed a heuristic algorithm based on a genetic algorithm to minimize the number of stations and the cycle time. Avikal et al. (2013) used the critical path method to minimize the number of stations and maximize labor productivity. Hamzadayi and Yildiz (2013) proposed a simulated annealing approach for minimizing the number of stations for mixed models u-shaped assembly line balancing problem.

Fattahi et al. (2014) presented a new formulation for the problem, where the objective is to minimize the number of stations. Jayaswal and Agarwal (2014) developed a simulated annealing approach to minimize the total annual cost of work station utilization, equipment operation, and assistant employment. Hazir and Dolgui (2015) proposed a bender decomposition algorithm for minimizing the cycle time. Ogan and Azizoglu (2015) developed a branch and bound algorithm for minimizing the total equipment cost. Alavidoost et al. (2016) used a two-phase interactive fuzzy programming approach to minimize the number of stations and cycle time under uncertainty. Nilakantan and Ponnambalam (2016) developed a particle swarm optimization approach for minimizing the cycle time and maximizing the production rate. Alavidoost et al. (2017) developed a modified genetic algorithm that deals with the problem under uncertainty. The objectives were to minimize the number of stations, maximize the fuzzy balance efficiency, and minimize the fuzzy idle time percentage.

Li et al. (2017) developed a heuristic approach based on multiple rules to minimize the cycle time. Oksuz et al. (2017) used an artificial bee colony algorithm and genetic algorithm to maximize line efficiency. Z. Li et al. (2018) proposed branch, bound and remember algorithm to maximize the number of stations. Zhang et al. (2019) developed a migrating birds optimization algorithm for minimizing the cycle time. Aydoğan et al. (2019) developed a particle swarm optimization algorithm to minimize the number of stations under uncertainty. Pınarbaşı (2021) dealt with the same problem discussed in this paper through linearizing the non-linear constraints and he used IBM ILOG CP solver to solve them.

The literature review shows that most of the researches have developed approaches to deal with the problem in its deterministic case. Hence, it appears that it is a solid motivation to discuss the uncertainty of the problem further. Therefore, this paper presents one of the uncertainty cases of the problem, which is the chance-constrained problem. In addition, it proposes an efficient GRASP algorithm as a new approach for solving the problem, where its results are compared with the results found in (Pınarbaşı, 2021) and proofed a high efficiency in terms of objective values and CPU times.

3. PROBLEM FORMULATION

According to the literature review, it appears that most researches have focused on deterministic processing time. In this paper, processing times of the tasks are represented as random variables that are normally distributed and each has an expected value $E(t_i)$ and variance $Var(t_i)$. The cycle time constraints of the problem are realized with a minimum probability. So, the problem can be reformulated as shown in Table 1.

$$Minimize \sum_{j=1}^n y_j \tag{1}$$

$$s.t. \sum_{j=1}^n x_{ij} = 1, \forall i = \{1, 2, \dots, n\} \tag{2}$$

Table 1. Notations

$i = \{1, 2, \dots, n\}$	The set of tasks
$j = \{1, 2, \dots, n\}$	The set of stations
t_i	The processing time
ct	The cycle time
$IP(i)$	The set of immediate predecessors of task i
$IS(i)$	The set of immediate successors of task i
$x_{ij} = \begin{cases} 1, & \text{if task } i \text{ is assigned to station } j \\ 0, & \text{otherwise} \end{cases}$	
<p>y_j is a variable that indicates the existence of station j :</p> $y_j = \begin{cases} 1, & \text{if } \sum_{i=1}^n x_{ij} \geq 1 \\ 0, & \text{otherwise} \end{cases}$	
<p>P_i indicates the status of assignment of the immediate predecessors of task i :</p> $P_i = \begin{cases} 1, & \text{if } \sum_{j=1}^n j x_{k_1j} \leq \sum_{j=1}^n j x_{ij}, \forall k_1 \in IP(i) \\ 0, & \text{otherwise} \end{cases}$	
<p>S_i indicates the status of assignment of the immediate successors of task i :</p> $S_i = \begin{cases} 1, & \text{if } \sum_{j=1}^n j x_{k_2j} \leq \sum_{j=1}^n j x_{ij}, \forall k_2 \in IS(i) \\ 0, & \text{otherwise} \end{cases}$	

$$P \left(\sum_{i=1}^n t_i x_{ij} \leq y_j ct \right) \geq \alpha_j, \forall j = \{1, 2, \dots, n\} \quad (3)$$

$$P_i + S_i \geq 1, \forall i = \{1, 2, \dots, n\} \quad (4)$$

$$x_{ij} \in \{0, 1\}, \forall i, j \quad (5)$$

The objective function (1) seeks to minimize the number of stations. The set of constraints (2) represents the assignment constraints, which ensures that each task is assigned in only one station. The set of chance constraints (3) ensures that the total processing time of any station doesn't exceed the cycle time with probability greater than or equal α_j . Such set of chance constraints can be converted to the following set of constraints to overcome the probabilities (Taha, 2017):

$$\sum_{i=1}^n E(t_i) x_{ij} + k_{\alpha_j} \sqrt{\sum_{j=1}^n \text{var}(t_i) x_{ij}} \leq y_j ct, \forall j = \{1, 2, \dots, n\}, \text{ where } k_{\alpha_j} \text{ is the } z\text{-score of } \alpha_j \quad (6)$$

The set of constraints (4) shows that each task has to be assigned after assigning either its immediate predecessors, or its immediate successors. Eventually, the set of constraints (5) ensures that the problem is an integer 0-1 programming problem.

4. THE PROPOSED ALGORITHM

The proposed approach for solving the problem is the greedy randomized adaptive search procedure. This algorithm is one of the meta-heuristics that searches for optimized solutions, through a set of iterations that contains a solution construction and a local search. The solution construction of this approach begins with a stochastic greedy rule that leads to a candidate solution. The next step of GRASP is to search around the candidate solution by using a local search. The final step is to compare the evaluation of the best local solution with the evaluation of the best solution found per all previous iterations.

4.1. Algorithm 1 (The Solution Construction)

The proposed approach begins with the solution structure, which can be developed as seen in algorithm 1. Figure 1 shows the flowchart of algorithm 1.

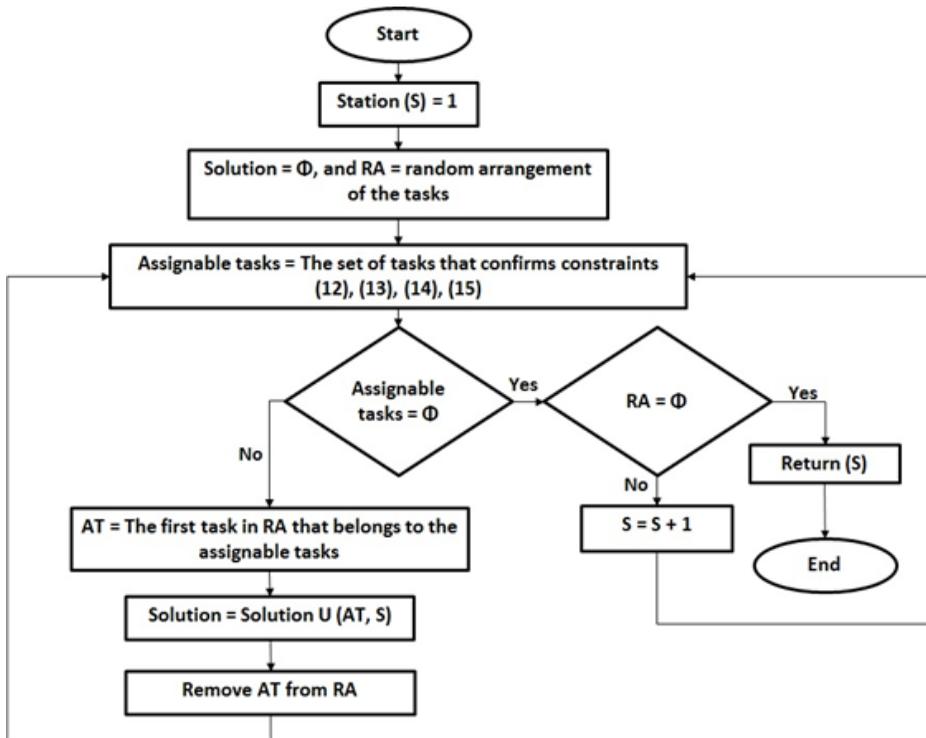
Algorithm 1 illustrates the random solution construction of the proposed algorithm. It begins by constructing a random arrangement (*RA*) of the tasks. The iterations of the algorithm find the assignable tasks according to the problem constraints, and then they choose the top task in the constructed random arrangement and assign it to the current open station. The assigned task then

Algorithm 1. Solution construction

```

Input: RA, Random arrangement of the problem tasks
Station, S = 1
Initiate Solution =  $\emptyset$ 
While RA is not empty DO
    Assignable tasks = The set of tasks that confirms constraints (2), (3), (4),
        and (5)
    If Assignable tasks =  $\emptyset$  and RA  $\neq \emptyset$  then set S = S + 1
    If Assignable tasks =  $\emptyset$  and RA =  $\emptyset$  then Break While loop
    AT = The first task in RA that belongs to Assignable tasks
    Solution = Solution  $\cup$  (AT, S)
    Remove AT from RA
End While
Return Solution
    
```

Figure 1. Algorithm 1 “Solution Construction”



will be eliminated from the constructed random arrangement set. A new station in the algorithm is to be opened when there are existed tasks in the constructed random arrangement set and no more of them can fit in the current open station. The solution of the algorithm will be returned when all tasks are assigned. Figure 1 shows the flowchart of algorithm 1.

4.2. Algorithm 2 (The Local Search)

According to the concept of GRASP, the constructed solution should be followed by a local search that tries to find the optimal local neighbor of it. The proposed mutation technique to find a neighbor is to swap the tasks of any station either with a forward station or backward station. After swapping, the sequence of the tasks will be presented to Algorithm 1 as *RA* to obtain another solution that is neighbor to the main random constructed solution. Algorithm 2 shows the local search of the proposed GRASP algorithm for solving the problem. Figure 2 shows the flowchart of the algorithm 2.

4.3. Algorithm 3 (GRASP)

After illustrating the constructed solution procedures, and the local search procedures, the steps of the proposed GRASP algorithm can be illustrated in Algorithm 3. Figure 3 shows the flowchart of algorithm 3.

5. EXPERIMENTAL DESIGN

The proposed algorithm is coded using python in a PC that has core 2 due CPU with 2.93 GHz and 4 GB rams. The proposed algorithm has four parameters, which are the number of constructed

Algorithm 2. Local search

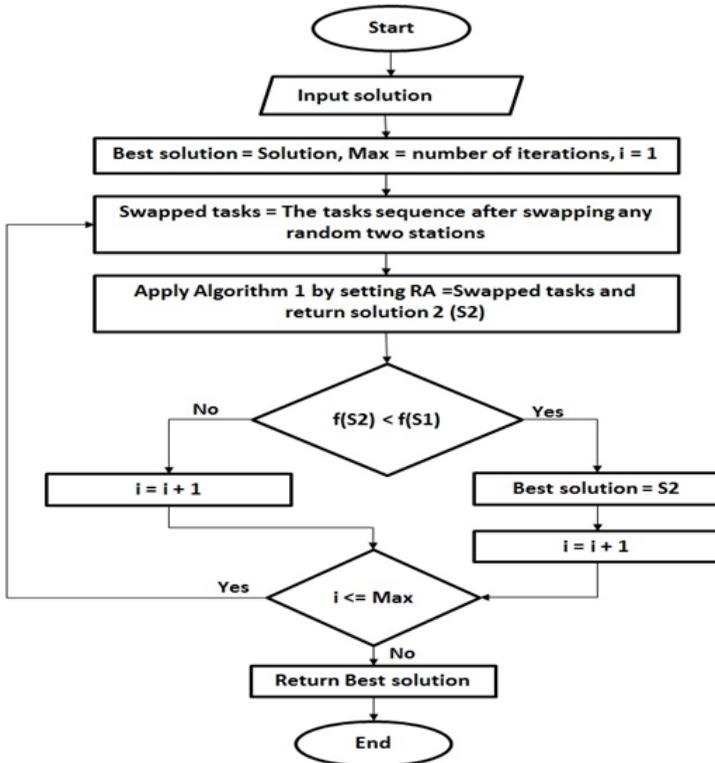
```

Input: Solution
Set Best Solution = Solution
Max = Number of iterations
i = 1
While i ≤ Max then
    Swap the tasks of any two random stations of Solution and save the output
    sequence of tasks in Swapped Tasks

    Run Algorithm 1 by setting RA = Swapped Tasks and return the output as
    Solution 2

    If  $f(\text{Solution } 2) < f(\text{Solution})$  then Best solution = Solution2
    i = i + 1
Return Best solution
    
```

Figure 2. Algorithm 2 “Local Search”

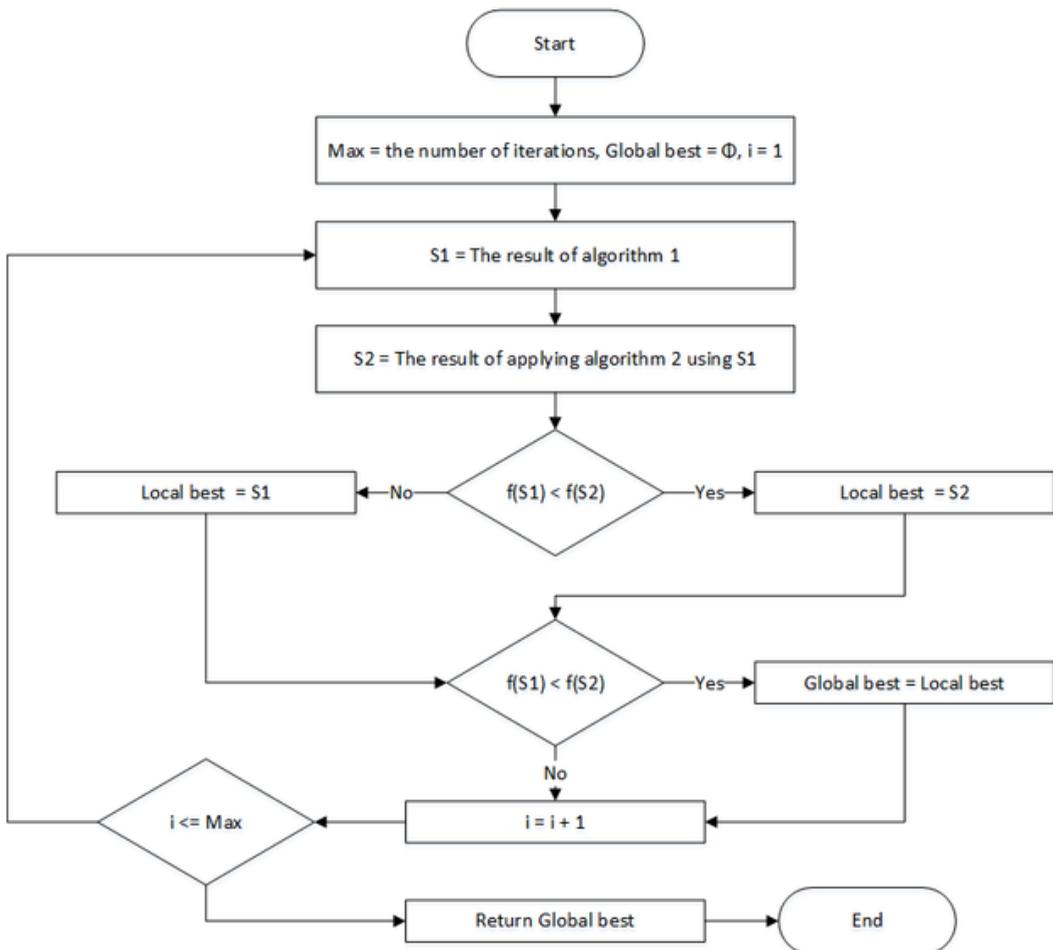


solutions (C), the number of local solutions (L), the swapping rate (S), and mutation function (M). The levels of parameter C are 5, 15, 20 solutions. The levels of parameter L are 10, 20, and 30. The levels of parameter S are 0.2, 0.3, and 0.4, where in such parameter the number of swapped tasks is obtained by multiplying the swapping rate by the number of tasks and rounding up the output to the

Algorithm 3. GRASP for solving CUALBP-1

```
Input: Max  
i = 1  
Global Best =  $\emptyset$   
while i ≤ Max then  
    Solution = Algorithm 1  
    Best Local Solution = Algorithm 2(Solution)  
    If  $f(\text{Best Local Evaluation}) < f(\text{Global Best Evaluation})$  then  
        Global Best = Best Local Solution  
    i = i + 1  
Return Global Best
```

Figure 3. Algorithm 3 “GRASP for Solving CUALBP-1”



nearest integer. The levels of parameter M are forward swapping (FS), backward swapping (BS), and bi-directional swapping (DS). The required trails to make full factorial design are $4^3 = 64$ trails. In Taguchi method, such number of trails can be reduced after calculating the degrees of freedom for each parameter to select the right orthogonal array. Equation (7) shows the required number of trails $N_{Taguchi}$, where L_i represents level i and NV is the number of levels:

$$N_{Taguchi} = 1 + \sum_{i=1}^{NV} (L_i - 1) \tag{7}$$

So, the required number of trails should be greater than or equal 9. Therefore, the selected orthogonal array for this experiment is L_9 , which is in Table 3.

The response in this experimental design includes the CPU time beside the objective function value as seen in equation (8). The selected test optimization problems are taken from a well-known benchmark found in <https://assembly-line-balancing.de/>. Table 4 shows the selected optimization problems and their associated cycle times and sizes. Table 5 shows the normalized results for each trail in each problem. The normalization of the results is done due to the variation of the objective functions from problem to another:

$$Response = \sum_{j=1}^n y_j - \frac{1}{CPU\ time} \tag{8}$$

Table 2. Notations

M	Mutation function
S	The number of swapped stations
L	The number of local search solutions
C	The number of constructed solutions

Table 3. The selected orthogonal array for experimental design

M	S	L	C
FS	0.2	10	5
BS	0.3	20	5
DS	0.4	30	5
DS	0.3	10	15
FS	0.4	20	15
BS	0.2	30	15
BS	0.4	10	20
DS	0.2	20	20
FS	0.3	30	20

Table 4. Test optimization problems

Problem	Cycle time	Size
JACKSON	9	11
MITCHELL	14	21
HESKIA	138	28
SAWYER30	25	30
ARC83	5048	83
ARC111	5755	111

Table 5. The normalized results for each trail

JACKSON	MITCHELL	HESKIA	SAWYER30	ARC83	ARC111
0.1269	0.1110	0.1224	0.1138	0.1166	0.1140
0.1089	0.1111	0.1226	0.1139	0.1099	0.1107
0.1092	0.1112	0.1076	0.1140	0.1105	0.1118
0.1091	0.1110	0.1076	0.1138	0.1094	0.1109
0.1093	0.1111	0.1073	0.1067	0.1119	0.1101
0.1095	0.1112	0.1084	0.1082	0.1103	0.1104
0.1090	0.1110	0.1090	0.1138	0.1094	0.1102
0.1089	0.1111	0.1077	0.1080	0.1107	0.1114
0.1090	0.1112	0.1075	0.1078	0.1113	0.1104

In order to obtain a robust setting that minimizes the response with a higher accuracy, the main effects for means and standard deviations are studied. Figure 4 shows the main effects plot for means and Figure 5 shows the main effects plot for standard deviations. From the figures, it can be stated that the optimized parameter levels can be summarized in Table 6, where each selected level has the minimum response and standard deviation.

6. COMPUTATIONAL RESULTS

The computational results show the implementation of the proposed GRASP algorithm in 48 adapted problems taken from <https://assembly-line-balancing.de/>. The problems vary in their sizes from 7 to 148 tasks. The comparison is done with a constrained programming approach (CP) proposed by Pınarbaşı (2021). The problems in the benchmark are deterministic. Therefore, the adaptation is done by considering the expected processing times of the tasks are the same as the original processing times in benchmark and the variances are calculated using a modified version of the method of Carraway (1989), which is mentioned in the introduction section. The reason for modifying the method is that it found that sometimes the generated variance causes violating the cycle time constraints. Therefore, the modified version of the method of Carraway (1989) is shown in equation 10, where it based on the generated value $Var_{test}(t_i)$ from either the low variances interval $\left[0, \left(\left(E(t_i)/4\right)^2\right)\right]$ or the high variances interval $\left[0, \left(\left(E(t_i)/2\right)^2\right)\right]$. The computational results table has a column for

Figure 4. Mean effects plot for means

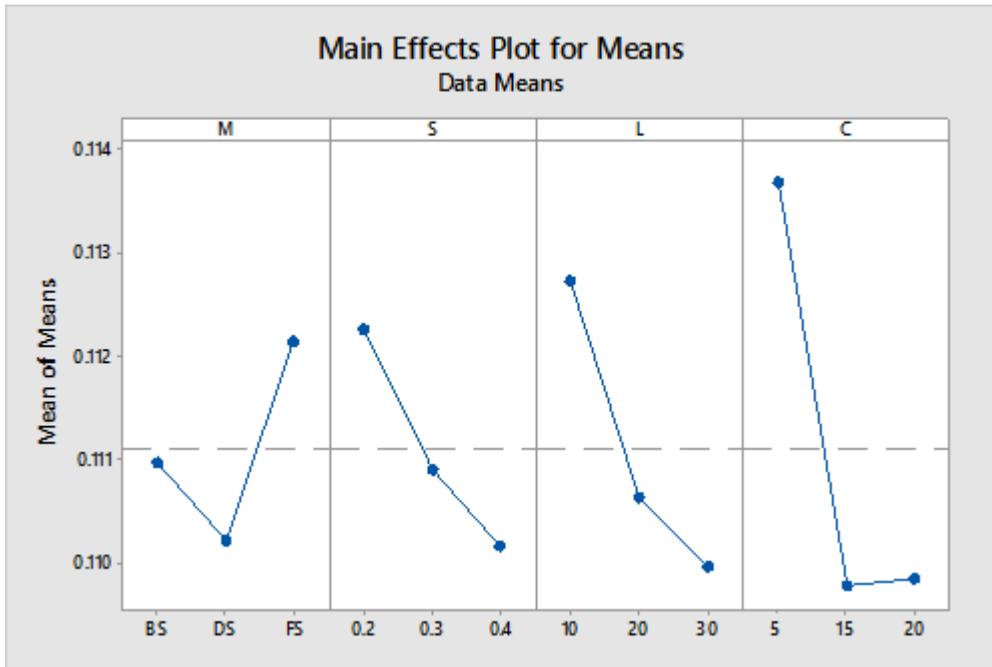


Figure 5. Mean effects plot for standard deviations

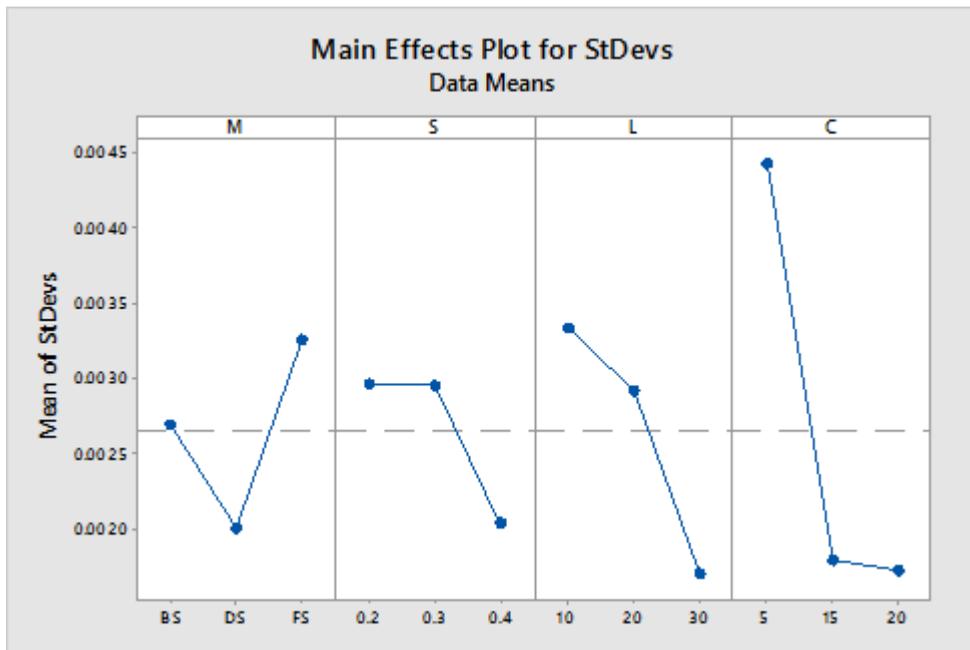


Table 6. The optimized parameters

Parameter	Level
M	DS
S	0.4
L	30
C	15

the deterministic lower bound for each problem to show how far the uncertainty results from the deterministic lower bound, which can be found by equation (11). The problems are solved in case of chance probabilities that are equal to 0.90, 0.95, and 0.975. Table 7 shows the computational results in case of low variances and Table 8 shows the computational results in case of high variances. Note: all CPU times in Tables 7 and 8 are in seconds:

$$Var_{test}(t_i) = rand(0,1) * \left(\frac{E(t_i)}{Var_{size}} \right)^2, Var_{size} = 2 \text{ or } 4 \quad (9)$$

$$Var(t_i) = \begin{cases} Var_{test}(t_i), & \text{if } Var_{test}(t_i) \leq ct \\ \left(\frac{ct - E(t_i)}{1.96} \right)^2, & \text{Otherwise} \end{cases} \quad (10)$$

$$LB = \frac{\sum_{i=1}^n E(t_i)}{ct}, \text{ where } x \text{ is the largest integer greater than } x \quad (11)$$

The proposed GRASP algorithm proves a high efficiency in terms of objective values and CPU times when compared to CP approach (Pınarbaşı, 2021). In case of low variances, the objective values shows that the GRASP algorithm is better than CP approach in 33 problems. In case of high variances, the GRASP algorithm is better than CP approach in 45 problems. In terms of CPU times, Pınarbaşı (2021) reported in his research that the minimum CPU time for the small sized problems, which are lower than or equal 70 tasks, is 0.01 and the maximum CPU time is 300. The large sized problems in CP approach have minimum CPU time approximately equal to the maximum CPU time, where both equal to 900. While in GRASP algorithm, the minimum CPU time is 0.01 and the maximum CPU time is 1.69 for all problems.

7. CONCLUSION

This paper presents a GRASP algorithm as a new approach for solving the U-shaped assembly line balancing problem under uncertainty. The uncertainty herein is related to having the processing times of the tasks as normally distributed random variables with known means and variances. Therefore, the problem is formulated as chance-constrained programming by considering that the cycle time

Table 7. Computational results (low variances)

Problem	ct	LB	$\alpha = 0.90$			$\alpha = 0.95$			$\alpha = 0.975$		
			CP	Number of stations (GRASP)	CPU time (GRASP)	CP	Number of stations (GRASP)	CPU time (GRASP)	CP	Number of stations (GRASP)	CPU time (GRASP)
B	8	4	5	5	0.01	5	5	0.01	5	5	0.01
MERTENS	10	3	4	3	0.01	4	3	0.00	4	3	0.01
MERTENS	15	2	3	2	0.01	3	2	0.00	3	2	0.00
MERTENS	18	2	2	2	0.01	2	2	0.00	2	2	0.00
BOWMAN8	20	4	6	5	0.01	6	5	0.01	5	5	0.01
JAESCHKE	6	7	8	8	0.01	8	8	0.01	8	8	0.01
JAESCHKE	7	6	7	7	0.01	7	7	0.01	7	7	0.01
JAESCHKE	8	5	7	6	0.01	7	6	0.01	7	6	0.01
JAESCHKE	10	4	5	4	0.01	5	4	0.01	5	4	0.01
JAESCHKE	18	3	3	3	0.01	3	3	0.02	3	3	0.01
JACKSON	9	6	7	6	0.03	7	6	0.03	7	6	0.01
JACKSON	10	5	7	5	0.01	7	5	0.01	7	5	0.01
JACKSON	13	4	5	4	0.01	5	4	0.01	5	4	0.01
JACKSON	14	4	4	4	0.01	4	4	0.01	4	4	0.01
JACKSON	21	3	3	3	0.01	3	3	0.01	3	3	0.01
MITCHELL	15	7	NFS	8	0.03	NFS	8	0.03	9	8	0.03
MITCHELL	21	5	6	6	0.02	6	6	0.02	6	6	0.03
MITCHELL	26	5	5	5	0.02	5	5	0.02	5	5	0.02
MITCHELL	35	3	4	3	0.25	4	3	0.07	4	3	0.14
MITCHELL	39	3	4	3	0.02	4	3	0.02	3	3	0.02
HESKIA	205	5	6	6	0.06	6	6	0.06	6	6	0.06
HESKIA	216	5	6	5	0.11	6	5	0.05	6	5	0.11
HESKIA	256	4	5	5	0.06	5	5	0.05	5	4	0.33
HESKIA	324	4	4	4	0.05	4	4	0.05	4	4	0.05
HESKIA	342	3	4	4	0.05	4	4	0.05	4	3	0.44
SAWYER30	33	10	15	11	0.11	14	11	0.19	14	11	0.06
SAWYER30	41	8	11	9	0.05	11	9	0.05	10	9	0.05
SAWYER30	47	7	10	8	0.05	9	8	0.05	8	8	0.05
KILBRID	79	7	9	8	0.11	8	8	0.11	8	8	0.11
KILBRID	92	6	7	7	0.10	7	7	0.11	7	7	0.11
KILBRID	110	6	6	6	0.12	6	6	0.11	6	6	0.11
KILBRID	138	4	5	4	0.83	5	5	0.10	5	5	0.11
KILBRID	184	3	4	3	0.52	4	4	0.10	4	3	0.21
TONGE70	207	17	22	19	0.61	20	19	2.79	20	19	3.41
TONGE70	234	15	19	17	0.29	19	17	0.63	18	17	0.30
TONGE70	320	11	14	12	0.27	13	12	0.28	13	12	0.28

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Table 7. Continued

Problem	ct	LB	$\alpha = 0.90$			$\alpha = 0.95$			$\alpha = 0.975$		
			CP	Number of stations (GRASP)	CPU time (GRASP)	CP	Number of stations (GRASP)	CPU time (GRASP)	CP	Number of stations (GRASP)	CPU time (GRASP)
LUTZ2	18	27	36	31	0.49	34	31	0.50	33	31	1.96
LUTZ2	21	24	30	26	0.45	29	26	0.46	28	26	0.92
LUTZ2	32	16	20	16	3.59	19	17	0.41	18	16	2.03
MUKHERJE	351	12	15	13	0.60	15	13	0.61	14	13	0.61
MUKHERJE	471	9	11	10	0.58	11	10	0.57	11	10	0.60
MUKHERJE	704	6	8	7	0.57	8	6	6.20	7	7	0.59
ARC111	9554	16	20	17	0.82	19	17	1.63	18	17	5.03
ARC111	11570	13	16	14	0.87	16	14	1.61	15	14	1.64
ARC111	15040	10	13	11	0.78	12	11	0.78	12	11	0.80
BARTHOLD	470	12	15	13	1.65	15	13	1.58	14	13	1.63
BARTHOLD	795	8	9	8	1.63	9	8	1.65	9	8	1.63
BARTHOLD	1127	5	7	6	1.71	6	6	1.67	6	6	1.67

Table 8. Computational results (high variances)

Problem	ct	LB	$\alpha = 0.90$			$\alpha = 0.95$			$\alpha = 0.975$		
			CP	Number of stations (GRASP)	CPU time (GRASP)	CP	Number of stations (GRASP)	CPU time (GRASP)	CP	Number of stations (GRASP)	CPU time (GRASP)
MERTENS	8	4	NFS	5	0.01	NFS	5	0.01	5	5	0.01
MERTENS	10	3	5	3	0.01	5	3	0.01	5	4	0.01
MERTENS	15	2	3	2	0.00	3	2	0.00	3	2	0.01
MERTENS	18	2	3	2	0.00	3	2	0.00	2	2	0.00
BOWMAN8	20	4	6	5	0.01	6	5	0.01	6	5	0.01
JAESCHKE	6	7	NFS	8	0.01	NFS	8	0.01	NFS	8	0.01
JAESCHKE	7	6	NFS	7	0.01	NFS	7	0.03	NFS	7	0.01
JAESCHKE	8	5	7	6	0.01	7	6	0.01	7	7	0.01
JAESCHKE	10	4	7	5	0.01	7	5	0.01	7	5	0.01
JAESCHKE	18	3	3	3	0.01	3	3	0.01	3	3	0.01
JACKSON	9	6	NFS	6	0.02	NFS	6	0.01	NFS	6	0.01
JACKSON	10	5	NFS	5	0.01	NFS	5	0.01	6	5	0.01
JACKSON	13	4	5	4	0.01	5	4	0.01	5	4	0.01
JACKSON	14	4	5	4	0.01	5	4	0.01	5	4	0.01
JACKSON	21	3	3	3	0.01	3	3	0.01	3	3	0.01
MITCHELL	15	7	NFS	8	0.03	NFS	8	0.03	NFS	8	0.03
MITCHELL	21	5	8	6	0.03	7	5	0.10	7	6	0.02

continued on following page

Table 8. Continued

Problem	ct	LB	$\alpha = 0.90$			$\alpha = 0.95$			$\alpha = 0.975$		
			CP	Number of stations (GRASP)	CPU time (GRASP)	CP	Number of stations (GRASP)	CPU time (GRASP)	CP	Number of stations (GRASP)	CPU time (GRASP)
MITCHELL	26	5	6	5	0.02	6	5	0.02	5	5	0.02
MITCHELL	35	3	4	3	0.14	4	4	0.02	4	4	0.02
MITCHELL	39	3	NFS	3	0.02	NFS	3	0.03	NFS	3	0.02
HESKIA	205	5	8	6	0.06	7	6	0.06	7	6	0.06
HESKIA	216	5	7	5	0.06	7	5	0.05	6	5	0.17
HESKIA	256	4	6	5	0.05	6	5	0.09	5	5	0.05
HESKIA	324	4	5	4	0.05	4	4	0.05	4	4	0.06
HESKIA	342	3	4	3	0.33	4	3	0.31	4	4	0.05
SAWYER30	33	10	NFS	11	0.06	NFS	11	0.05	NFS	11	0.11
SAWYER30	41	8	13	9	0.05	13	9	0.05	11	9	0.05
SAWYER30	47	7	11	8	0.05	11	8	0.05	10	8	0.05
KILBRID	79	7	NFS	8	0.11	NFS	8	0.11	NFS	8	0.11
KILBRID	92	6	8	7	0.11	8	7	0.11	8	7	0.11
KILBRID	110	6	7	6	0.11	7	6	0.11	6	6	0.10
KILBRID	138	4	6	5	0.10	6	5	0.11	5	5	0.10
KILBRID	184	3	4	4	0.10	4	3	0.32	4	4	0.11
TONGE70	207	17	NFS	19	4.01	NFS	19	1.54	NFS	20	0.30
TONGE70	234	15	NFS	17	0.60	NFS	17	0.60	NFS	17	0.29
TONGE70	320	11	16	12	0.28	15	12	0.28	14	12	0.28
LUTZ2	18	27	40	30	0.49	39	31	3.48	35	31	0.46
LUTZ2	21	24	32	26	2.30	32	26	5.49	29	26	2.71
LUTZ2	32	16	24	17	0.41	23	17	0.41	20	17	0.41
MUKHERJE	351	12	18	13	0.62	17	13	0.61	16	13	0.61
MUKHERJE	471	9	13	10	0.60	13	10	0.59	12	10	0.60
MUKHERJE	704	6	9	7	0.59	9	7	0.59	8	7	0.58
ARC111	9554	16	24	17	4.20	22	17	1.69	21	17	2.53
ARC111	11570	13	20	14	0.81	19	14	1.68	17	14	0.81
ARC111	15040	10	15	11	0.79	15	11	0.79	13	11	0.79
BARTHOLD	470	12	18	13	1.64	17	13	1.65	16	13	1.65
BARTHOLD	795	8	11	8	1.62	10	8	1.63	10	8	1.63
BARTHOLD	1127	5	8	6	1.65	7	6	1.67	7	6	1.69

constraints as probabilistic constraints that are restricted by predetermined chance probability. After optimizing the parameter of the algorithm using Taguchi method, the computational results are done to compare the proposed algorithm with CP approach proposed by Pınarbaşı (2021). The results of the proposed GRASP algorithm show high efficiency in terms of objective values and CPU times. The future points of research may consider the following points:

- Solving other types of assembly line balancing problems under uncertainty using the same algorithm.
- Adding space constraints that are related to having area for each task.
- Considering that each station has chance probability differs from the other stations, since there are operators more skillful than the others and they should have different chance probability.
- Solving the same problem in case that the number of stations is given and the cycle time is required to be minimized.
- Solving the problem in case that both of the number of stations and the cycle time are not given and the required objective is to maximize the line efficiency.

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