Cuckoo Search Approach for Cutting Stock Problem

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***Abstract*—Cutting Stock Problem has been used in many industries like paper, glass, wood and etc. Cutting Stock Problem has helped industries to reduce trim loss and at the same time meets the customer's requirement. The purpose of this paper is to develop a new approach which is Cuckoo Search Algorithm in Cutting Stock Problem. Cutting Stock Problem with Linear Programming based method has been improved down the years to the point that it reaches limitation that it cannot achieve a reasonable time in searching for solution. Therefore, many researchers have to turn to metaheuristic algorithms as a solution to the problem which also makes these algorithms become famous. Cuckoo Search Algorithm is selected because it is a new algorithm and outperforms many algorithms. Hence, this paper intends to experiment the performance of Cuckoo Search in Cutting Stock Problem.**

***Index Terms*—Cuckoo search algorithm, swarm intelligence, cutting stock problem, optimization.**

I. Introduction

The Cutting-Stock Problem (CP) is an optimization problem, or more specifically, an integer linear programming problem. It arises from many applications in industry, for examples, paper, glass, steel, furniture, leather and others. Not only cutting stock problem helps in saving material and also in optimizing the usage of resources, but also being part of the green manufacturing research purpose [1]. Importance of this research had been supported by many academic publications throughout this ten years period. One of the academic papers is written by G. Belov *et al* which implemented a cutting plane algorithm (CPA) in CP [2]. Based on the paper, this research attempts is to experiment Cuckoo Search Algorithm (CSA) in CP.

However, there is still limitation in Cutting Stock Problem (CSP) in meeting industrial requirement due to multiple sizes demanded from the customers which create multiple patterns that cause Cutting Stock Problem unable to search for the best solution. The best solution of Cutting Stock Problem is minimizing the wastage and at the same time meeting customer's requirement. According to previous work, Linear Programming based method is used to overcome this problem, but unfortunately the wastage unable to be minimized. Therefore, Cuckoo Search is well suitable to replace the Linear Programming based method and assist Cutting Stock Problem to search the best solution.

Manuscript received July 2, 2014; revised September 6, 2014. This work was supported in part by the Universiti Teknikal Malaysia Melaka (UTeM) and the Ministry of Higher Education (MOHE) of Malaysia under the Research Acculturation Grant Scheme (RAGS).

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II. Cutting Stock Problem

Cutting stock problem is defined as an integer decision variable for each possible pattern. It is also known as a layout plan to predict the final result of the cutting patterns. The main objective is to minimize the trim loss or cost value. The other objectives of cutting stock problem are to minimize the number of stocks and to minimize the number of partially finished item [3].

The concept of CSP is to find the optimized cutting patterns along with the number of stock roll which is used to meet the demand of ordered rolls which is also known as customer orders, and also to bring the cost for the wastage to its least amount plus other controllable factors. In order to achieve the goal, the total amount of the roll width cut from each stock roll must not be more than the usable width of the stock roll. The formula for cutting stock is shown as follows [4]:

Let R_i be the nominal order requirements.

W_i be the rolls of width, where $i = 1, \ldots, m$, to be cut from the stock rolls of usable width, UW.

RL_i is the lower bounds on the order requirement, whereas RU_i is the upper bounds on the order requirement

$$\text{Min} \sum_J T_j X_j \tag{1}$$

$$\text{Subject to } RL_i \leq \sum_J A_{ij} X_j \leq RU_i \ \text{ for all } i \tag{2}$$

$$X_j \geq 0 \text{ and integer,} \tag{3}$$

where A_{ij} is the number of rolls of width W_i, to be slit from each stock roll that is processed using pattern j. In order for the elements, A_{ij}, $i = 1, \ldots, m$, to constitute a feasible cutting pattern, the following restrictions must be satisfied:

$$\sum_J A_{ij} W_j \leq UW, \tag{4}$$

$$A_{ij} \geq 0 \text{ and integer,} \tag{5}$$

X_j is the number of stock rolls to be slit using pattern j, and T_j the trim loss incurred by pattern j,

$$T_j = UW - \sum_J A_{ij} W_j, \tag{6}$$

III. Metaheuristic Algorithms

Modern Metaheuristic algorithms are primarily influenced by biological nature. It seems that biological systems work in such a way that produces a remarkable result towards adaptation, reliability and robustness in the dynamic and even hostile environments in spite of individual simplicity. Metaheuristic algorithms are capable in dealing with a huge

DOI: 10.7763/IJIEE.2015.V5.518

total population in iteration and for each population's individual, the function is evaluated and a fitness function is assigned [5]. Besides, metaheuristic algorithms are capable of solving non-differentiable nonlinear-objective functions. As for the classical optimization, it will be hard to get the solutions of these functions. Therefore, concept of metaheuristic algorithms works in a way that the intensification desires to search for the current best solution and choose the best among the candidates or solutions. On the other hand, metaheuristic algorithm is able to venture the search space effectively due to its diversification. Examples of metaheuristic algorithms are Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing, Ant Colony Optimization and etc.

IV. Cuckoo Search Algorithm

Based on paper by X. Yang, Cuckoo Search Algorithm has three laws [6]. Firstly, an egg laid by a cuckoo at a time, and then leave its egg in a random nest which is chosen by the cuckoo; secondly, for the eggs to proceed to the next generation, it has to be the best nest and cuckoo's egg is of high quality; lastly, the present number for host nests is fixed and the probability for the host to find out the egg belongs to a cuckoo is $Pa \in [0, 1]$. In this situation, there are two possibilities; the host may dump cuckoo's egg; leave the present nest to build new nest. Based on this concept, the new nests with new randomly solutions replace the nest, n and the fraction, Pa of nest, and n is able to estimate the last assumption.

For maximization problem, a solution's fitness is corresponding to the objective function. Let each egg be a solution and let the new solution be a cuckoo's egg, the objective is to replace a poorer result of solution in the nests with the new solutions which results in better egg. Furthermore, this algorithm can handle a nest own with numerous number of eggs represent a set of solutions; this situation is a complex case.

$$x^{(t+1)}i = x(t)\, i + \alpha \oplus L\acute{e}vy(\lambda) \text{ [6]} \quad (7)$$

The above L ́evy flight equation $x^{(t+1)}$ is a new solution and i is a cuckoo. The new solution is generated when the L ́evy flight is performed. Based on the paper, α must be greater than 0, α is the step size that is corresponded with the scales of the interests' problem, $\alpha = 1$ is usually used [6]. The L ́evy flight equation is a stochastic equation which is proposed for random walk. A random walk is called as a Markov chain, its future status and location are highly depending on the present location which is the first time in L ́evy flight equation and the changing probability is the second time. The product $\oplus$ means entry wise multiplications. L ́evy flight provides a random walk and L ́evy distribution that has an infinite variance with an infinite mean provides the random step length.

$$\text{L'evy} \sim u = t^{-\lambda},\ (1 < \lambda \leq 3) \text{ [6]} \quad (8)$$

These steps are able to produce a process of random walk process with a power law step-length distribution and a heavy tail. L ́evy should generate some of the new solutions walk around the best solution which is obtained. In this situation is able to speed up the local search. Far field randomization should generate a substantial fraction of the new solutions and the distance of the locations from the current best solution should be sufficiently far, in order to protect the system from stucking in a local optimum.

V. Experimental Work

A. Design Cutting Stock Problem Model

In designing a cutting stock problem (CSP), the objectives are to minimize the trim loss and at the same time the outcome of summation of the patterns' rolls must meet the requirement order or customer's order. In other words, the reduction of wastage is subjected to cutting roll to meet customer's order or order requirement. The problem is formulated as linear program shown below [4].

$$\text{Min} \sum_J T_j X_j \quad (9)$$

$$\text{Subject to } RL_i \leq \sum_J A_{ij} X_j \leq RU_i \text{ for all } i \quad (10)$$

$$X_j \geq 0 \text{ and integer,} \quad (11)$$

A_{ij} is the number of rolls of width W_i
R_i = the nominal order requirements.
UW = stock rolls of usable width.
W_i = the rolls of width, where $i = 1, \ldots, m$, to be cut from the stock rolls of usable width, UW.
RL_i = the lower bounds on the order requirement,
RU_i = the upper bounds on the order requirement
X_j = the number of stock rolls to be slit using pattern j
j= pattern

In some cases, there are papers prefer to use this formula [7].

$$\text{Min} \sum_{j\in J} w_j\, x_j \quad (12)$$

$$\text{Subject to } \sum_{j\in J} a_{ij} x_j = N_i \text{ for all } i = 1, 2, 3, \ldots, n \quad (13)$$

$$X_j \geq 0 \text{ and integer,} \quad (14)$$

where,
J = pattern of cutting stock
a_{ij} = Number of pieces of item i
n = Number of orders
x_j = Number of runs of pattern j
w_j = Waste per run of pattern j
N_i = Number of pieces of item i
J = all patterns of cutting stock

In this situation, both linear programming formulas are under optimization field. This is where Cuckoo Search Algorithm will apply in this linear programming. CSP model is designed using Matlab based on its constraints which must be fulfilled. The following shows the constraints that must be satisfied [4].

$$\sum_J A_{ij} W_j \leq UW, \quad (15)$$

$$A_{ij} \geq 0 \text{ and integer}, \quad (16)$$

$$T_j = UW - \sum_J A_{ij} W_j, \quad (17)$$

T_j is the trim loss incurred by pattern j

A_{ij} is the number of rolls of width W_i

UW = stock rolls of usable width.

W_i = the rolls of width, where i = 1, …, m, to be cut from the stock rolls of usable width, UW.

J = pattern

Calculations were done before proceed with Matlab modeling in order to check the Matlab result. Consider a situation where the stock rolls are 50 inch wide and the requirement orders are summarized, 1 final of width 10 inch, 1 final of width 50 inch, 1 final of width 30 inch, 1 final of width 15 inch, 2 finals of width 25 inch.

Let

UW= 50 (inch);

a_{ij} = 10 (inch), a_{2j} = 50 (inch), a_{3j} = 30 (inch)

a_{4j} = 15 (inch), a_{5j} = 25 (inch)

The table shows the acceptable cutting patterns which is less than stock rolls inch, UW.

TABLE I: ACCEPTABLE CUTTING PATTERNS

j	1	2	3	4
A_{1j}	1	0	0	0
A_{2j}	0	1	0	0
A_{3j}	0	0	1	0
A_{4j}	0	0	1	0
A_{5j}	0	0	0	2

When j = 1

$$T_j \text{ (Trim Loss)} = UW - (a_{1j})$$
$$T_j = 50 - 10 = 40$$

When j = 2

$$T_j = UW - (a_{2j})$$
$$T_j = 50 - 50 = 0$$

When j = 3

$$T_j = UW - [(a_{3j}) + (a_{4j})]$$
$$T_j = 50 - [(30) + (15)] = 5$$

When j = 4

$$T_j = UW - 2[(a_{5j})]$$
$$T_j = 50 - [2(25)] = 0$$

Total trim loss

$$T_j = 40 + 5 = 45$$

B. Design Cuckoo Search Algorithm in Cutting Stock Problem

The previous design of Cutting Stock Problem is based on its constraint which is not completed; hence, Cuckoo Search Algorithm is applied to fulfil the whole concept of Cutting Stock Problem. Basically, the purpose of Cuckoo Search Algorithm is to search for the feasible solution or best fitness in Cutting Stock Problem. The best fitness is referring to low wastage or trim loss which is obtain from the Cutting Stock Problem's constraint. Cuckoo Search Algorithm is designed in accordance to Cutting Stock Problem's formula in (12), (13) and (14).

In other words, in exploring the fitness which is obtained from constraint of Cutting Stock Problem, Cuckoo Search Algorithm is subjected to the formula above by finding the lowest wastage or trim loss as its best fitness and at the same time the outcome of summation of the rolls of patterns must meet the requirement order or customer's order.

Cuckoo Search Algorithm is characterized by Xin-She Yang in three rules:

- Each cuckoo lays one egg at a time, and dumps its egg in randomly chosen nest
- The best nests with high quality of eggs will carry over to the next generations
- The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability $pa \in [0, 1]$.

The flow chart in Fig. 1 shows Cuckoo Search Algorithm in searching the feasible solution.

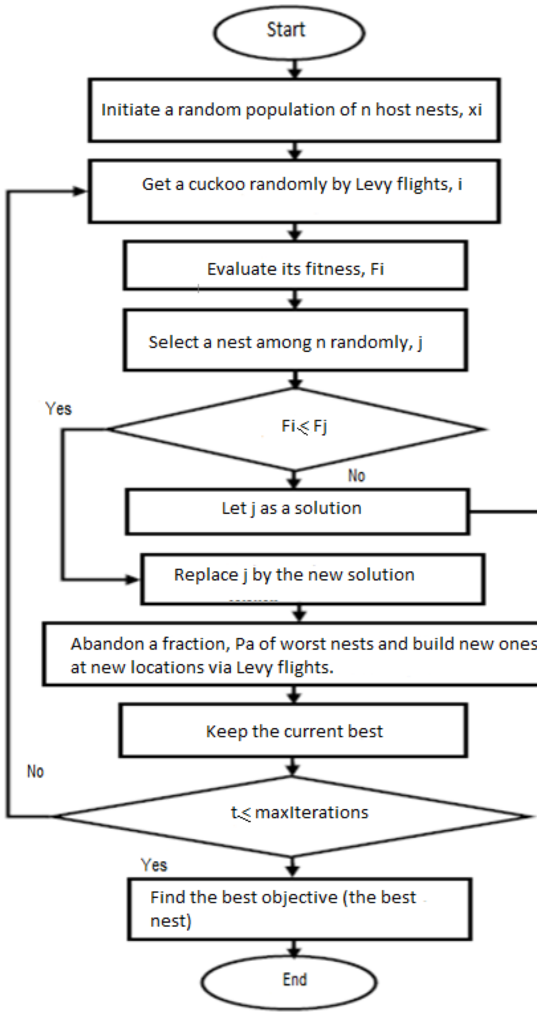

Fig. 1. Flow chart for Cuckoo Search Algorithm [8].

VI. RESULTS AND DISCUSSION

In this section, there are two sets of data collections done in order to obtain the optimal solution which is the minimum wastage. Cuckoo Search Algorithm (CSA) consists of 4 parameters which is Pa (probability), β (beta), n (nest) and N_i (iteration). These four parameters play an important role in contributing to the optimal solution. In other words, to obtain the optimal solution, the values of the four parameters must be determined. Therefore, the two sets of data collections needed to be carried out through the designed coding are β versus *Pa* and *n* versus N_i. It is started with β versus pa to determine the best value for β and *Pa* and at the same time, N_i and *n* is set as constant. Once the value for β and *Pa* is found, it is applied in *n* versus N_i which is the final step to determine the optimal solution. Before the CSA parameter is determined, input data of Cutting Stock Problem are considered too. The input data of Cutting Stock Problem are width of stock rolls, demand width and number of demand width.

In this case, width of stock rolls is 5600 mm wide and its number is unlimited. As for the demand width and number of demand width are shown in Table II. This set of values is based on paper [9].

TABLE II: DEMAND WIDTH AND NUMBER OF DEMAND WIDTH [8]

Demand Width	*Number of Demand Width*
1380	22
1520	25
1560	12
1710	14
1820	18
1880	18
1930	20
2000	10
2050	12
2100	14
2140	16
2150	18
2200	20

Hence, the parameters of Cutting Stock Problem remain constant throughout the data collection.

A. β versus Pa

β versus *Pa* is carried out first which is shown in Table III, to determine the best combination of values for β and *Pa* that contribute to the best fitness. In this case, the best fitness is the lowest wastage, N_i and *n* is set as constant with the value of 1000 and 25 respectively. In Table III, all the fitness is an average of 10 values which obtained from the same combination of β and *Pa*. For an example, in Table IV, β = 0.5 and *Pa* = 0.1 which gives the fitness of 58200, to get this fitness, β = 0.5 and *Pa* = 0.1 are used to run 10 times in the program, in order to get the average fitness of 10 fitness. The tested values of *pa* are from 0.1 to 0.9 and the tested values of β are from 0.5 to 2.5.

TABLE III: B VERSUS P_A

β/Pa	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.5	58200	58200	57640	57640	58760	58200	57080	55400	56520
0.75	55960	57080	57640	56520	58200	56520	56520	57080	55960
1	58200	57080	57640	57640	58200	58200	57640	56520	55960
1.25	58760	58760	59320	59320	57640	60440	57080	57640	57640
1.5	59320	60440	59880	58200	57080	59880	59320	57640	57640
1.75	61560	58200	61000	61000	61000	59880	61000	58760	60440
2	61000	62120	60440	59880	61000	61560	59320	58200	59320
2.25	59880	60440	61000	60440	62680	59880	57640	57640	58760
2.5	61000	61000	61560	60440	62120	61000	61560	59880	59880

From Table III, the worst fitness is 62680 which is obtain from *Pa* = 0.5 and β = 2.25. Furthermore, the most common fitness is 57640 and 58200 which appear 13 times and 10 times respectively in the table. As for the best fitness also known as the lowest wastage is 55400 which obtained from *Pa* = 0.8 and β = 0.5. Based on the best fitness in β versus *Pa*, *Pa* = 0.8 and β = 0.5 are applied as a constant in *n* versus N_i.

Based on Table III it seems that fitness changes according to β and *Pa*. As β increases, it increases the possibility of getting poor fitness that is more than 60,000. The possibility of poor fitness appears from β = 1.25 to β = 2.5. For example, when β = 1.25, there is one poor fitness which is 60440; when β = 1.5, there is one poor fitness which is 60440; when β = 1.75, there is 6 poor fitness which is 61560, 61000, 61000, 61000, 61000 and 60440; when β = 2, there is 5 poor fitness which is 61000, 62120, 60440, 61000 and 61560; when β = 2.25, there is 4 poor fitness which is 60440, 61000, 60440 and 62680; when β = 2.5, there is 7 poor fitness which is 61000, 61000, 61560, 62120, 61000 and 61560. On the contrary, *Pa* shows a different function compared to β, it seems that *Pa* increases, a low possibility of poor fitness appears. *Pa* = 0.1 to *Pa* = 0.9 is observed; when *Pa* = 0.1, there is 3 poor fitness which is 61540, 61000 and 61000; when *Pa* = 0.2, there is 4 poor fitness which is 60440, 62120 and 61000; when *Pa* = 0.3, there is 4 poor fitness which is 61000, 60440 and 60440; when *Pa* = 0.5, there is 4 poor fitness which is 61000, 61000, 62680 and 62120; when *Pa* = 0.6, there are 3 poor fitness which is 60440, 61560 and 61000; when *Pa* = 0.7, there is 2 poor fitness which is 61000 and 61560; when *Pa* = 0.8, there is no poor fitness; when *Pa* = 0.9, there is one poor fitness which is 60440. Therefore, to obtain a feasible solution, the value of *Pa* must be high; on the other hand, value of β must be low. In this case, the best fitness is obtained from *Pa* = 0.8 which is high and β = 0.5 which is low.

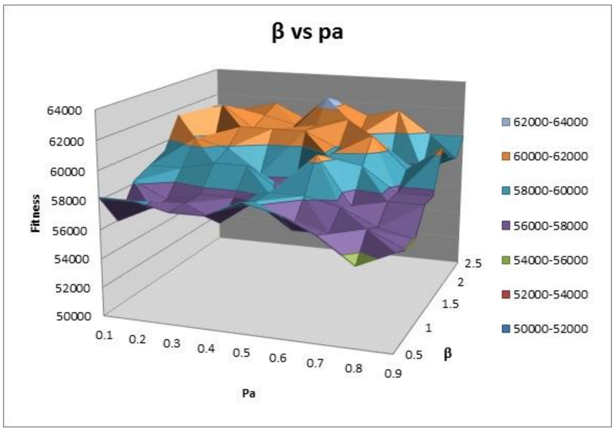

Fig. 2. β versus *Pa*.

B. N versus N_i

The set of data collection in Table IV is the final step to determine the optimal solution which also known as the minimum wastage. The value for β = 0.5 and *Pa* = 0.8 are obtained from the previous Table III are used in *n* versus N_i as constant values. In Table IV, nest with the value from 10 to 100 is used to test with iteration of 100 to 10000. Each combination of nest and iteration revealed the values for “Best”, “Mean” and “Worst”. “Best” is known as the best fitness or minimum wastage which is selected from the 10 values that obtained from the same combination of nest and iteration which runs 10 times. "Mean" is defined as the average fitness of the 10 values that obtained from the same combination of nest and iteration. "Worst" is the worst fitness or highest wastage which is selected from the 10 values that obtained from the same combination of nest and iteration. For an example, in Table IV, iteration = 100 and nest = 10 shows that "Best" equals to 63240, "Mean" equals to 65480 and "Worst" equals to 68840. To obtain this result, iteration = 100 and nest = 10 are used to run 10 times in the program, to obtain 10 values. From the 10 values, the minimum wastage or highest wastage is selected for "Best" and "Worst", the average of the 10 values is for "Mean".

From Table IV, the best mean is 49240 which is from the combination of N_i = 10000 and n = 50 and n = 75, and its best fitness is 46440 and its worst fitness is 52040. As for the mode mean is 55960, it appears in the combination of N_i = 1000 with n = 50 or n = 75, and also the combination of N_i = 500 with n = 75 or n = 100. The best fitness of mode mean is 52040 and the worst fitness of the mode mean is 57640. As for the worst mean is 65480 from the combination of N_i = 100 and n = 10, and it consists of best fitness with value of 63240 and worst fitness with the value of 68840.

TABLE IV: *N* VERSUS N_i

n/Ni	100		500		1000		5000		10000	
10	Best	63240	Best	57640	Best	57640	Best	52040	Best	52040
	Mean	65480	Mean	59880	Mean	58200	Mean	54280	Mean	53720
	Worst	68840	Worst	63240	Worst	63240	Worst	57640	Worst	57640
25	Best	63240	Best	57640	Best	52040	Best	46440	Best	46440
	Mean	64360	Mean	58200	Mean	56520	Mean	51480	Mean	50920
	Worst	68840	Worst	63240	Worst	57640	Worst	52040	Worst	52040
50	Best	57640	Best	52040	Best	52040	Best	46440	Best	46440
	Mean	62120	Mean	57080	Mean	55960	Mean	51480	Mean	49240
	Worst	63240	Worst	57640	Worst	57640	Worst	52040	Worst	52040
75	Best	57640	Best	52040	Best	52040	Best	46440	Best	46440
	Mean	62680	Mean	55960	Mean	55960	Mean	51480	Mean	49240
	Worst	63240	Worst	57640	Worst	57640	Worst	52040	Worst	52040
100	Best	57640	Best	52040	Best	46440	Best	46440	Best	46440
	Mean	61000	Mean	55960	Mean	52040	Mean	50920	Mean	49800
	Worst	63240	Worst	57640	Worst	52040	Worst	52040	Worst	52040

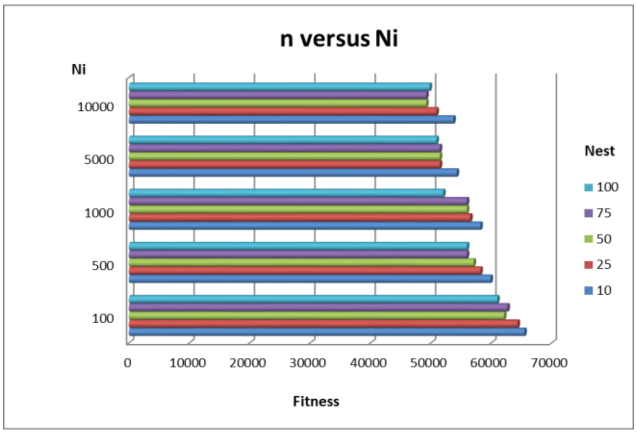

Fig. 3. *N* versus N_i versus fitness.

In Fig. 3, it is observed that as the nest, n increases, and the value of "Mean" decreases. This shows that the optimal solution is improved, when nest increases. For example, when N_i = 100, as n increases from 10 to 100, the value of "Mean" decreases. Same goes to N_i = 500, N_i = 1000, N_i = 5000 and N_i = 10000, when n increases from 10 to 100, the value of "Mean" also decreases. Furthermore, iteration, N_i also has the same properties as nest that when iteration is increased, the optimal solution is improved. Iteration, N_i is observed from 100 to 10000; it seems that the value of "Mean" decreases regardless of the value of nest. In this case, the optimal solution is found in the combination of N_i = 10000 with n = 50 or n = 75, which has a high number of iteration and a high value of nest. Literally, the current optimal solution is capable to be improved, by increasing the iteration and nest. Unfortunately, the increase of nest and iteration leads to a longer duration in obtaining the result. Therefore, the nest and iteration are limited to a certain range in this data collection.

C. *Without Cuckoo Search Algorithm (CSA)*

The Table V shows the set of data collection which is obtained from Cutting Stock Problem without applying CSA. The purpose is to compare CSA in Cutting Stock Problem with the absent of CSA in Cutting Stock Problem. Since the absent of CSA in Cutting Stock Problem, the only parameter for Cutting Stock Problem to be altered is iteration. And the iteration is set in range of values from 100 to 10000 which is the same range as CSA. Every value of iteration is run 10 times to obtain the average value of "Best", "Mean" and "Worst". From Table V, the best mean is 68840 which is from the iteration of 5000 and 10000, its best fitness is 68840 and its worst fitness is 68840. While, the mode mean is 68840 which appears in the iteration of 5000 and 10000. And the best fitness of mode mean is 68840 and the worst fitness of the mode mean is 68840. As for the worst mean is 75560 from the iteration of 100 and it consists of best fitness with value of 74440 and worst fitness is 80040.

TABLE V: WITHOUT CSA

Iteration	*100*	*500*	*1000*	*5000*	*10000*
Best	74440	68840	68840	68840	68840
Mean	75560	73880	72200	68840	68840
Worst	80040	74440	74440	68840	68840

Furthermore, Table VI is the comparison of CSA and without CSA with three aspects are focused that is "Best mean", "Mode mean" and "Worst mean". The result of "Best mode", "Mode mean" and "Worst mean" in Table VI is obtained from the Table IV and Table V respectively.

TABLE VI: COMPARISON WITH CSA AND WITHOUT CSA

	CSA		Without CSA	
Best mean	Best	46440	Best	74440
	Mean	49240	Mean	75560
	Worst	52040	Worst	80040
Mode mean	Best	52040	Best	68840
	Mean	55960	Mean	68840
	Worst	57640	Worst	68840
Worst mean	Best	63240	Best	68840
	Mean	65480	Mean	68840
	Worst	68840	Worst	68840

It is expected that the overall result of CSA is better than without CSA in Cutting Stock Problem in order to prove the CSA in Cutting Stock Problem model is valid. Based on Table VI, the best mean, mode mean and worst mean of CSA shows a significant result compared to without CSA. Since Cuckoo Search Algorithm in Cutting Stock Problem shows a drastic effect compare with Cutting Stock Problem without algorithm, this shows that the designed CSA in Cutting Stock Problem is valid.

VII. Conclusion

The approach of Cuckoo Search Algorithm (CSA) is proposed in Cutting Stock Problem to explore the performance of the proposed algorithm. Cuckoo Search Algorithm in Cutting Stock Problem has been validated and compare with without CSA, Genetic Algorithm (GE) and Evolutionary Programming (EP). Based on result and comparison, the performance of Cuckoo Search Algorithm is superior to without CSA, but also have a same performance as GE and EP. This is partly because of the extra parameters in Cuckoo Search Algorithm which is pa and β that causes the performance better than without CSA. Furthermore, in accordance to the result, *Pa* and β increase the frequentation of appearance of the best fitness or minimum wastage, while the other parameters; nest and iteration are capable of improving the feasible solution. This shows that Cuckoo Search Algorithm is able to reveal the best fitness frequently, at the same time; the fitness is able to be improved too. This shows that the motivation of this paper is achieved by minimize the wastage and meeting demand order of customer.

Acknowledgment

The authors would like to thank Universiti Teknikal Malaysia Melaka (UTeM) and the Ministry of Higher Education (MOHE) of Malaysia for its financial support from Research Acculturation Grant Scheme (RAGS) RAGS/2013/FKE/TK02/03/B00026 for sponsoring the resources for this research.

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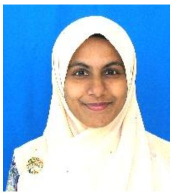

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