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Improving for Drum_Buffer_Rope material flow management with attention to second bottlenecks and free goods in a job shop environment

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Abstract- *Drum–Buffer–Rope is a theory of constraints production planning methodology that operates by developing a schedule for the system's first bottleneck. The first bottleneck is the bottleneck with the highest utilization. In the theory of constraints, any job that is not processed at the first bottleneck is referred to as a free good. Free goods do not use capacity at the first bottleneck, so very little attention is given to them in the Drum–Buffer–Rope literature. The objective of this paper is to present a methodology that improves the Drum–Buffer–Rope material flow management with attention to the second bottleneck and free goods. This paper presents a comparative analysis of Drum–Buffer–Rope material flow management and the proposed methodology in a job shop environment. To study the impact of free goods and the second bottleneck on the performance of the DBR method, 18 job shop simulation models were developed and data analysis was done for each simulation model. Lead time and throughput are the system performance measurement output parameters. The simulation result shows that the proposed methodology significantly improved the lead time and throughput.*

Keywords- *Drum–Buffer–Rope; Theory of constraints; Free goods; Bottleneck*

I. INTRODUCTION

The theory of constraints (TOC) is a management methodology developed by Goldratt in the mid-1980s (Goldratt & Fox, 1986). Every system must have at least one constraint. If this were not true, a real system would make unlimited profit. So a constraint is anything that prevents a system from achieving higher performance (Goldratt, 1988). The existence of constraints represents opportunities for improvement. Because constraints determine the performance of a system, a slow elevation of the system's constraints will improve its performance, so TOC views constraints as positive.

In the early 1990s, Goldratt improved TOC by an effective management philosophy on improvement based on identifying the constraints to increase throughput. TOC's approach is based on a five-step process (Goldratt, 1990):

1) Identify the system constraint(s).
2) Exploit the constraint(s).
3) Subordinate all other decisions.
4) Elevate the constraint.
5) Do not let inertia become the system constraint.

The TOC is often referred to as Drum–Buffer–Rope (DBR), as developed by Goldratt in the 1980s (Goldratt & Fox, 1986). DBR uses the protective capacity to eliminate the time delays to guarantee that the bottleneck resource stays on schedule and customer orders are shipped on time (Chakravorty & Atwater, 2005). DBR uses the drum or constraint to create a schedule based on the finite capacity of the first bottleneck, and a buffer which protects the drum scheduling from variation. The rope is a communication device that connects the capacity constrained resource (CCR) to the material release point and controls the arrival of raw material at the production system (Schragenheim & Ronen, 1990).

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Rope generates the timely release of just the right materials into the system at just the right time (Wu, Morris & Gordon, 1994).

This paper begins with a description of DBR scheduling logic and the literature review that has led up to this study. Then the proposed methodology is explained. Following the proposed methodology section, simulation models are explained and the resulting study is carried out. The final section presents a discussion and conclusions drawn from the study and directions for future research are identified.

II. LITERATURE REVIEW

The literature review showed that the TOC has two major components. First, it focuses on the five steps of on-going improvement, the drum–buffer–rope (DBR) scheduling, and the buffer management information system. The second component of TOC is an approach for solving complex problems called the thinking process (Rahman, 1998).

Sarkar and Kumar proposed an integrated model by combining the Laplace criterion and TOC into a single evaluation model in a multi-product constraint resource environment (Sarkar & Kumar, 2008). Pegels and Watrous applied TOC to a bottleneck operation in a manufacturing plant and eliminated the constraint that prevented productivity at the plant (Pegels & Watrous, 2005). Tanhaei and Nahavandi improved the TOC approach to determine the optimal product mix in a two constraint resource environment (Tanhaei & Nahavandi, 2012). Bozzone introduced the theory of delays and claimed that this name is better than TOC because all constraints create delays but not all delays are caused by constraints (Bozzone, 2001). Graham explored the relationship between the ideas developed in the third novel, critical chain by Goldratt (Goldratt, 1997) and the PERT/CPM approach. He showed the application of the theory of constraints on how management deals with human behaviour in constructing and managing the project network (Rand, 2000).

Many papers compared the TOC flow management with material requirement planning (MRP) and just in time (JIT). For example, Gupta and Snyder (Gupta & Snyder, 2009) compared TOC (i) with MRP, (ii) with JIT, and (iii) with both MRP and JIT together, and concluded that TOC competes effectively against MRP and JIT. Sale and Inman compared the performance of companies under the TOC and JIT approaches. They indicated that the greatest performance and improvement accrued under the TOC approach (Sale & Inman, 2003). Cheraghi et al. compared seven different production control systems in a flow shop environment. The result showed that no single production control system is best under all conditions and it depends not only on the type of manufacturing strategy but also on the values of the input parameters (Cheraghi, Dadashzadeh & Soppin, 2008).

Babu et al. generalized the TOC approach by integer linear programming (ILP) to increase the throughput with minimum investment. They collected the data from an automobile manufacturing industry to validate their model (Babu, Rao & Maheshwaran, 2006). Steele et al. studied a simulation model with the objective of comparing the MRP and DBR systems. Their result showed that different systems provide different responses to customer demand and also that the DBR performance was clearly better than MRP implementation (Steele, Philipoom, Malhotra & Fry, 2005). Ray et al. compared three alternatives: TOC, ILP and their proposed approach. They considered an integrated heuristic model by using an analytic hierarchy process (AHP) in a multiple resource environment. Their numerical result showed that the proposed approach is better than TOC and ILP (Ray, Sarkar & Sanyal, 2010).

DBR develops the production schedule by applying the first three steps in the TOC process (Rabbani & Tanhaei, 2015). Betterton and Cox investigated the DBR scheduling and flow control method in a flow shop environment. They compared the DBR model and a similar push system (Betterton & Cox, 2009). Georgiadis and Politou proposed a dynamic time-buffer control mechanism in both internal and external shop environments to support the decision-making on time- buffer policies. The result revealed the insensitivity of time-buffer policies to key factors related to demand, demand due date and operational characteristics such as protective capacity and production times (Georgiadis & Politou, 2013).

In DBR, any job that is not processed at the system's first bottleneck is referred to as a free good. Since free goods are not processed at the system's first bottleneck, very little attention has been given to these jobs in DBR (Chakravorty & Verhoeven, 1996). Chakravorty and Atwater found that the performance of DBR is very sensitive to changes in the level of free goods release into the operation and claimed that schedulers of a job shop environment using DBR need to be aware of how the orders for these items are scheduled (Chakravorty & Atwater, 2005).

Schragenheim and Dettmer introduced Simplified Drum–Buffer–Rope theory (SDBR). SDBR is based on the same concept as traditional DBR. The only difference is that in SDBR the market demand is the major system constraint (Schragenheim & Dettmer, 2000). Lee et al. examined two conditions that were handled with SDBR solutions. They considered the following characteristics and solved an example: (1) the capacity constraint resource (CCR) is not always located in the middle of the routing; (2) multiple CCRs can exist rather than the assumption of just one CCR (Lee, Chang, Tsai & Li, 2010). Chang and Huang provided a simple, effective way of DBR to determine the due dates and release dates of orders and jobs. They claimed that managers could easily use the proposed model to effectively manage their orders to meet customer requirements (Chang & Huang, 2013).

After this review of the literature on TOC and DBR material flow management, the following results were determined:

1) The TOC considers constraint resources, but in the context of multiple constraint resources, it does not provide the optimal solution for product-mix decisions and sometimes the solution is infeasible. Real-world problems have multiple bottlenecks and therefore finding the optimum feasible solutions from TOC is impossible.

2) DBR material flow management pays very little attention to free goods and operates by developing a schedule for the system's first bottleneck. In other words, it ignores the impact of other bottlenecks in scheduling.

3) While the DBR method is much simpler than the older Optimized Production Technology (OPT) algorithm, for many production environments, especially job shop environments, the better methodology can be adopted.

The major contribution of this study is to propose a methodology that considers free goods and a second bottleneck in the job shop environment. In the proposed method, lead time and throughput are the system performance measurement output parameters and the simulation result shows the improvement of these output parameters in the proposed methodology.

III. PROPOSED METHODOLOGY

The proposed methodology is presented in four sections. In the first section, the details of the simulation model are provided. Next, the proposed methodology is described. In the third section, the model construction and simulation result are discussed and in the fourth section data analysis is done.

A. Simulation Model

By using the Arena simulation package, a 12-station job shop producing 10 different product lines was simulated. This job shop model was developed for four reasons. First, the model had a complex operation. Second, the model presented a job shop with 10 jobs and different routings. Third, performance data related to the model were developed by making the model closer to the real world. Fourth, the following assumptions were considered in the model:

1) Probability of failure was considered for each machine.
2) Setup time was considered for each machine and setup was performed in batches.
3) Operators were considered for each machine
4) Product demand was considered weekly.
5) Each job had a separate process time and a separate setup time.
6) The capacity of production lines was less than the product demand; in other words, all products were sold, so the amount of product demand was not important.
7) In the simulation, the amount of material released to the production lines was commensurate with the likely demand for each product.

The effectiveness of the proposed approach designed for the job shop is proved through a set of experiments that are implemented in three parts: for small-sized problems, medium-sized problems and large-sized problems. Eighteen different models (6 models for each part) were generated for this study. For tuning this category of problem, different experiments with different sets of parameters were solved. Different models were generated for this study by varying the processing and setup times of the machines, the machines' up time and down time probability, the routing sequence of the products, probability of failure, product demand and the way of releasing material and so on.

An example of a problem instance is given here. The job shop consisted of a total of 14 machines grouped into 12 work stations. The two work centres (4 and 8) consisted of two machines each.

The details of the jobs and their specific routings through the shop are provided in Table 1.The routing sequence for each job specified how a product moved through the shop from material release to the finished good. For example, job 6 first visited station 2, then station 5, followed by stations 6, 2 and finally 10. Once released into the shop, orders were sequenced through each station on a first come first serve basis, consistent with the DBR scheduling system.

The processing time distribution and setup time distribution for each job were uniform, as provided in Table 2. For example, the processing time distribution of job 1 on the first station was (2,3), meaning that the processing time had a continuous uniform distribution over the interval [2,3].

TABLE I. Details of the jobs

Jobs	Routing sequence	Sale price	Lead time cost per minute
1	1,4,3,6,7,8,10,12	450	0.325
2	2,4,5,4,8,6,9,11	470	0.4
3	1,2,4,9,12	400	0.55
4	1,4,3,2,7,10,11	490	0.3
5	1,3,5,7,3,8,9,10	410	0.85
6	2,5,6,2,10	500	1.1
7	2,3,6,8,10	520	0.6
8	1,3,8,7,5,11	230	0.7
9	1,6,5,2,8,9	450	1.3
10	1,2,3,5,7,12	460	0.4

TABLE II. Processing time distribution and setup time distribution of each job (min)

Machines	12	11	10	9	8	7	6	5	4	3	2	1	
Total of machine	1	1	1	1	2	1	1	1	2	1	1	1	
													jobs
Process time	(3,7)	_	(3,5)	-	(3,7)	(3,5)	(8,10)	_	(3,4)	(4,5)	-	(2,3)	1
	_	(3,5)	-	(5,6)	(3,5)	-	(7,8)	(3,7)	(4,5)	-	(1,2)	-	2
	(3,4)	-	-	(3,4)	-	-	-	-	(3,4)	-	(3,4)	(3,4)	3
	-	(2,4)	(2,4)	-	-	(2,4)	-	-	(2,4)	(6,8)	(5,7)	(2,3)	4
	-	-	(3,5)	(4,6)	(3,5)	(4,6)	-	(3,5)	-	(4,6)	-	(2,4)	5
	-	-	(3,5)	-	-	-	(3,5)	(2,4)	-	-	(1,3)	-	6
	-	-	(3,6)	-	(3,6)	-	(2,4)	_	-	(3,5)	(2,4)	-	7
	-	(2,4)	-		(2,4)	(3,5)	-	(2,4)	-	(3,5)	-	(3,4)	8
	-	-	-	(3,6)	(3,6)	-	(2,4)	(1,3)	-	-	(2,4)	(3,5)	9
	(3,5)	-	-	-	-	(3,5)	-	(4,6)	-	(3,5)	(4,6)	(3,5)	10
Setup time	(2,3)	-	(1,2)	-	(2,3)	(1,2)	(2,3)	-	(1,2)	(.5,1.5)	-	(1,2)	1
	-	(1,2)	-	(1,2)	(1,2)	-	(1,2)	(2,3)	(2,3)	-	(1.5,2.5)	-	2
	(1,2)	-	-	(1,3)	-	-	-	-	(1,2)	-	(1,3)	(1,3)	3
	-	(2,3)	(1.5,3)	-	-	(2,3)	-	-	(1.5,3)	(1,2)	(2,3)	(2,3)	4
	-	-	(1,2)	(2,3)	(1,2)	(2,3)	-	(1,1.5)	-	(2,3)	-	(1,2)	5
	-	-	(1,3)	-	-	-	(1,3)	(2,3)	-	-	(1,2)	-	6
	-	-	(1,3)	-	-	(1,3)	-	-	(2,3)	(1,2)	-	-	7
	-	(1,3)	-	-	(1,3)	_	(1,2)	-	(2,3)	-	(1,2)	(1,2)	8
	-	-	-	(2,3)	-	(2,3)	(1,2)	-	-	(2,3)	(1,2)	(2,3)	9
	(2,3)	-	-	-	(2,3)	-	(1,2)	-	(1,3)	(2,3)	(1,2)	(1,2)	10

The machines' up time and down time are uniform and are provided in Table 3.

In this model based on the processing times at each station, the first bottleneck was station 6 and its utilization was 93% and the second bottleneck was station 2 and its utilization was 89%.

B. Description of Proposed Methodology

The proposed methodology was implemented in the following steps:

1) The first bottleneck resource and the second bottleneck resource were determined. (i.e. the primary constraint resource and the second most heavily utilized resource).
2) Jobs arrived in a pre-shop queue where the routings and the processing times were determined and waited for release into the shop.
3) Any job not processed at the first bottleneck (free goods) and any job not processed at the second bottleneck were determined and released into the shop without attention to buffer sizes.
4) Any job processed at the first bottleneck but not processed at the second bottleneck was released into the shop with attention to the first buffer size.
5) Any job not processed at the first bottleneck (free goods) but processed at the second bottleneck was released into the shop with attention to the second buffer size.
6) Any job processed at the first bottleneck and the second bottleneck was released into the shop with attention to the first buffer size and the second buffer size.
7) Optimum values of the first buffer size and the second buffer size were determined through OptQuest (Arena comes with a package called OptQuest that uses heuristics known as Tabu search and scatter search to move around intelligently in the input control space and tries to converge quickly to an optimal point).
8) Under the proposed mechanism, jobs waited in the order review queue. When the respective buffer size was reduced, the next job was removed from the order review queue and released into the shop.

In this approach, the simulation result indicated that there was a significant improvement in the proposed method compared with the DBR method.

C. Model Construction and Simulation Result

After the DBR model and proposed model were developed, a warm-up period was determined, because the production model was in a steady-state simulation. This means that the model started out with empty entities and all resources were idle. If the model were initializing empty and idle in a simulation where things eventually became congested, the output data for some period of time after initialization would tend to understate the eventual congestion; this means that the data would be biased as low. To remedy this, we let the model warm up for a while until it appears that the effects of the artificial conditions have worn off. At that time, the statistical accumulators become clear and are started anew. Based on the work in process (WIP), as can be seen in Figure 1, the model required 120 minutes to reach a steady-state condition.

The simulation was run for 2880 minutes, which was one work week, because it was assumed that demand was weekly. The number of replications was determined through the following formula:

$$h_0 = t_{n-1,1-\alpha/2} \frac{s}{\sqrt{n}} \quad (1)$$

This led to the following as an approximate required sample size to achieve a confidence interval with half width equal to a pre-specified value h. We obtained, with each simulation run, the mean values and the associated 95% half width of each variable. Thus the significance level was 5%, or stated another way, the alpha value was 0.05. n is the number of simulation replications in the sample; s is the sample standard deviation; and $t_{n-1,1-\alpha/2}$ is the critical value from t tables.

TABLE III. Machines up time and down time (hour)

machines	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Up time	(1,2)	(2,3)	(2,3)	(1,2)	(2,3)	(1,2)	(2,3)	(1,2)	(2,4)	(2,3)	(1,2)	(2,3)
Down time	(.5,1)	(1,2)	(.5,1)	(.5,.75)	(1,1.5)	(.5,1)	(1,2)	(.5,1)	(1,2)	(.5,1)	(.5,.75)	(1,1.5)

$$n \cong n_0 \frac{h_0^2}{h^2} \tag{2}$$

where n_0 is the number of initial replications we have and h_0 is the half width we get from the formula. With n_0= 10 the simulation was run and calculation showed that 16 replications were suitable, so the final simulation was run with 16 replications.

The system's performance was measured using two different criteria. One criterion was the throughput of the system and the other was the average lead time of the product. Table 4 shows the throughput result of the simulation models for the DBR method and the proposed method.

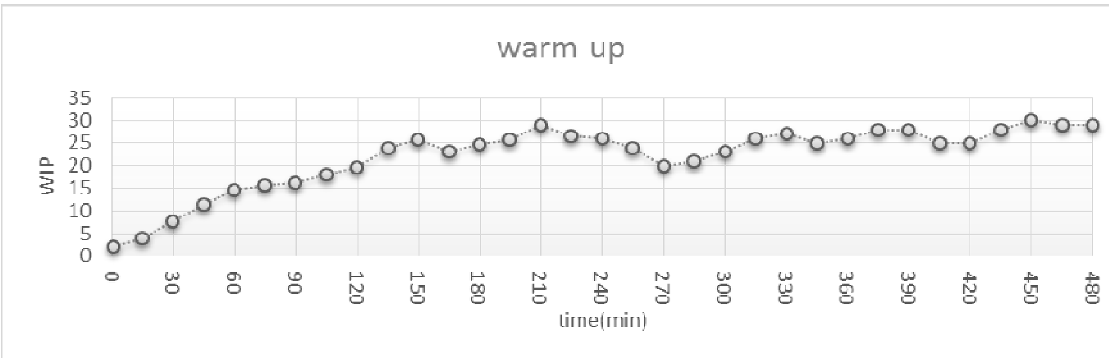

Fig. 1. Work in Process

TABLE IV. Throughput result

DBR method solution								
no. replication	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Throughput	347000	342320	348800	336900	345200	۳۷۰۵۴۰	355440	350120
no. replication	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Throughput	353320	344100	318000	331160	372260	359020	359320	336700
proposed method solution								
no. replication	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
throughput	36978-	361080	353080	349200	354680	378100	356120	367980
no. replication	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
throughput	353440	365020	364820	355340	370960	341660	363440	381660

TABLE V. Lead time cost result

DBR method solution								
no. replication	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Lead time cost	190755,5	219048,08	258993,26	222518,99	188794,6	174636,59	183103,13	187571,58
no. replication	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Lead time cost	196939,76	198122,12	186699,05	201987	219323,85	143099,37	210006,16	155278
proposed method solution								
no. replication	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Lead time cost	104262,9	190154,8	186798,34	227884,88	211305,13	194574,05	186840,65	168783,19
no. replication	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Lead time cost	170079,44	186138,9	180337,09	167674,48	182193,83	134749,73	168950,53	206482,88

In the next section data analysis is done.

D. Data Analysis

The Independent-Samples t-test procedure compares means for two groups of cases (the DBR method solution and proposed method solution). The result of data analysis for throughput is shown in Table 6.

The result shows that the proposed methodology significantly improved the throughput.

The result of data analysis for the lead time cost is shown in Table 7.

The result shows that the proposed methodology did not significantly improve the lead time.

IV. SIMULATED MODELS WITH THE PROPOSED METHOD

To study the impact of free goods and the second bottleneck on the performance of the DBR method, 18 job shop simulation models were developed. Job shop models were developed with different numbers of jobs and different numbers of stations, and data analysis was done for each simulation model to determine the performance of the proposed method in terms of throughput and lead time compared with the DBR method. Table 8 shows the result of the t-test for equality of means in the 18 simulation models.

*Significant at $\propto = 0.05$

TABLE VI. Result of data analysis for throughput

t_test for equality of mean				
	T	**Df**	**Sig**	**Mean Difference**
Throughput	-3.129	30	0.004	-13755

Significant at $\propto = 0.05$

TABLE VII. Resuolt of data analysis for lead time

t_test for equality of mean				
	T	**Df**	**Sig**	**Mean Difference**
Lead time	1.685	30	0.102	16854.13063

Significant at $\propto = 0.05$

TABLE VIII. Result of simulation models

no. model	**Throughput**		**t_test**	**Lead time cost**		**t_test**
	DBR	**proposed**		**DBR**	**Proposed**	
1	180294.29	182024.29	.459	102099.51	90757.64	**.044**
2	220106.67	216463.33	.287	86324.98	77267.31	**.048**
3	221590.67	230888	**.001**	230757.91	212743.47	.195
4	267369	254355	.053	273476.95	242343.45	**.002**
5	156245.71	176658.57	**0**	306982.97	299481.03	.49
6	321787.5	317777.5	.426	264627.81	253657.43	**.035**
7	266292.86	262307.14	.055	262222.53	254610.65	**.05**
8	265638	274671	**.028**	269480.3	269300.59	.767
9	347892.5	361647.5	**.004**	196054.82	182950.68	.102
10	183780	186325.71	.414	102622.69	104649.1	.815
11	215308.33	215328.33	.996	118171.83	100620	**.047**
12	219796	227528	**.037**	261457.6	240287.03	.24
13	268770	274269	.541	281466.01	262035.31	**.045**
14	159020	161161.43	.507	328285.77	320907.38	.464
15	301217.5	300657.5	.953	310849.58	275375.3	**.018**
16	279867.14	270811.43	.479	278693.09	251072.97	**.002**
17	235262	244684	**.037**	224002.02	196154.46	**.015**
18	338640	355723.75	**.005**	244208.68	224625.08	.081

*Significant at $\propto = 0.05$

As can be seen, bold numbers in the t-test column are significant. Fig. 2 shows the significant difference of the lead time cost in the DBR method and the proposed method in the 18 simulation models.

Fig. 3 shows the significant difference of throughput in the DBR method and the proposed method in the 18 simulation models.

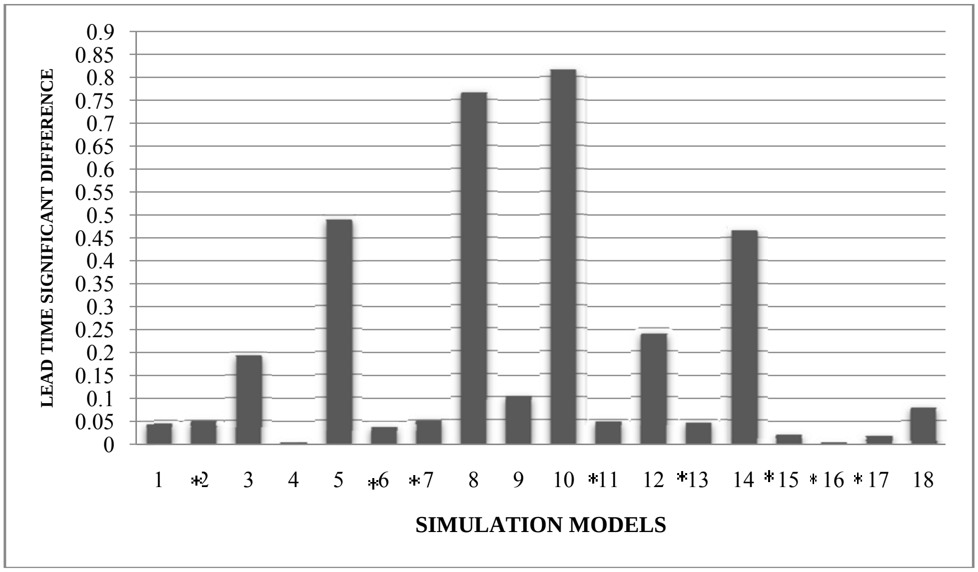

Fig. 2. Lead Time Cost Significant Difference

*Significant at $\propto = 0.05$

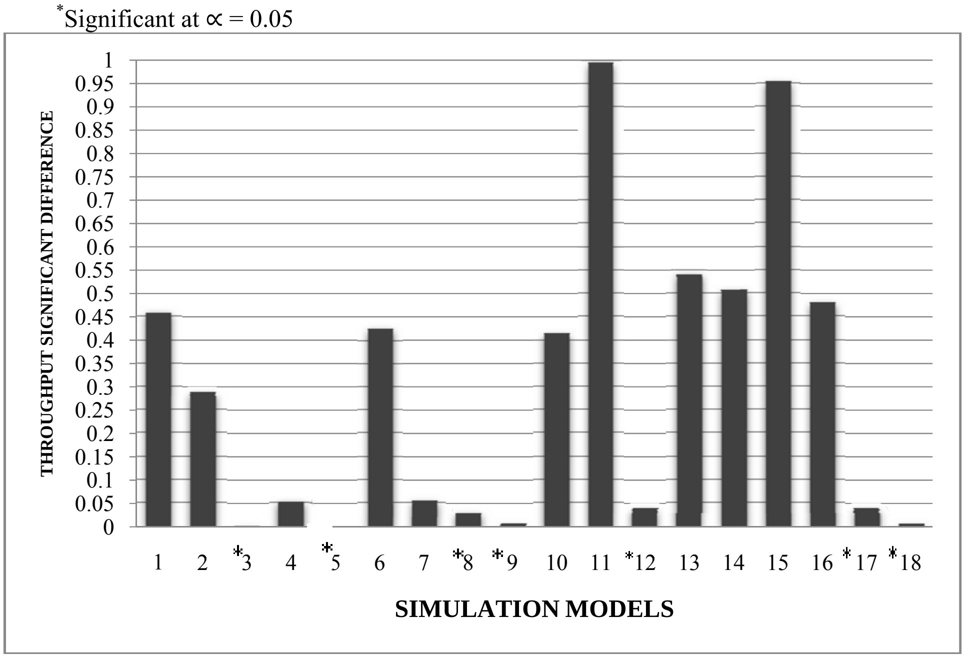

Fig. 3. Throughput Significant Difference

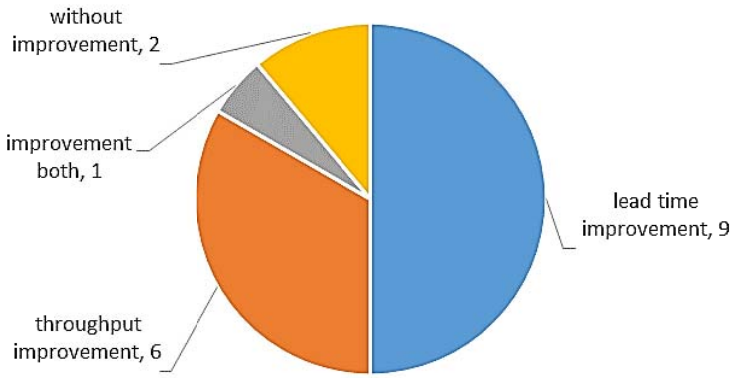

Fig. 4. Result of data analysis

We used the t-test based on a 5% significance level (an alpha of 0.05) to calculate the significant differences of the cost of the lead time and throughput in the DBR method and the proposed method. When these significant differences have a t-test value of less than 0.05, it is significant at alpha= 0.05.

After data analysis, as shown in Fig. 2 and Fig. 3, the following four results were obtained:

1) Data analysis showed that in 9 simulation models, the proposed methodology significantly improved the lead time.
2) Data analysis showed that in 6 simulation models, the proposed methodology significantly improved the throughput.
3) Data analysis showed that in 1 simulation model, the proposed methodology significantly improved the lead time and throughput.
4) Data analysis showed that in 2 simulation models, the proposed methodology did not significantly improve the lead time and throughput.

Fig. 4 shows the result of the data analysis.

V. RESULT STUDY

The study of the simulation models and the location of the first and second bottlenecks in the simulated production line showed the following four cases for each of four results.

1. In the models, the proposed methodology significantly improved the lead time, and the location of the second bottleneck in the production line was after the location of the first bottleneck. This reduced the lead time in the proposed method, because in the DBR method, jobs were released into the shop only with attention to the first buffer size. So, after being released into the shop and passing from the first bottleneck station, jobs were likely to wait behind the second bottleneck station. This waiting time increased the lead time, while in the proposed method jobs were released into the shop with attention to both the first buffer size and the second buffer size. So, after being released into the shop, they did not wait behind the second bottleneck station and the lead time was decreased. In this situation, the proposed methodology did not significantly improve the throughput, because jobs were released into the shop with attention to both the first buffer size and the second buffer size. This waiting time in the pre-shop queue decreased the throughput.
2. In the models, the proposed methodology significantly improved the throughput, and the location of the second bottleneck in the production line was before the location of the first bottleneck. This increased the throughput in the proposed method, because in the DBR method, free goods were ignored. So all jobs, even any job not processed at the first bottleneck (free goods), waited in the pre-shop queue until being released into the shop with attention to the first buffer size. This unnecessary waiting time of the free goods in the pre-shop queue decreased the throughput, while in the proposed method, any job not processed at the first bottleneck (free goods) and any job not processed at

the second bottleneck were released into the shop without attention to the buffer size. This increased the throughput in the proposed method. In this situation, the proposed methodology did not significantly improve the lead time, because in the DBR method, the optimum amount of the first buffer was determined. The amount of the first buffer was determined from the material release point to the site of the first bottleneck, so the optimum first buffer size considered the optimum amount of buffer size for all stations before the first bottleneck station. This means that the optimum amount of the second buffer was considered in the DBR method. So the condition existing in the first case was removed and the proposed method did not significantly improve the lead time.

3. In one model, the proposed methodology significantly improved the throughput and lead time, and the location of the second bottleneck in the production line was after the location of the first bottleneck. So as in the first case, the lead time was increased. The model study showed that in this model, there were many free goods and many jobs not processed at the second bottleneck. So at first, they were released into the shop without attention to the first buffer size and the second buffer size. This increased the throughput in the proposed method.
4. In two models, the proposed methodology did not significantly improve the throughput and lead time, and the location of the second bottleneck in the production line was before the location of the first bottleneck. Therefore, as in the second case, the proposed methodology did not significantly improve the lead time. In this situation, the proposed methodology did not significantly improve the throughput, because the models studied showed that in these two models, there were almost no free goods. So the proposed methodology that attended to the free goods was not effective. This situation rarely happens because the production system is job shop.

VI. DISCUSSION AND CONCLUSION

The paper presented a methodology that improves the Drum–Buffer–Rope material flow management with attention to the second bottleneck and free goods. In this work, a comparative analysis of the Drum–Buffer–Rope material flow management and the proposed methodology in a job shop environment was improved. The lead time and throughput were the system performance measurement output parameters. As this study verified, attention to the second bottleneck and free goods improved the amount of throughput and lead time, thereby improving the performance of the DBR scheduling system too. In addition, this study found that the greater the number of free goods, the greater the importance of the proposed methodology in maximizing the throughput and minimizing the lead time. To study the impact of free goods and the second bottleneck on the performance of the DBR method, 18 job shop simulation models were developed and data analysis was done for each simulation model. The simulation result indicated that there is a significant improvement in the proposed method compared with the DBR method.

It should be noted that, until now, very little attention has been given to the most heavily utilized resources except the first bottleneck in the DBR literature, while, as shown in this paper, for many production environments and especially job shop environments, the DBR methodology can be improved. So, there is scope for further research in the job shop environment with attention to other bottlenecks.

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