IMPROVING THROUGHPUT AND COMPLETION DATE ESTIMATION IN HIGH PRECISION COMPONENT MANUFACTURER USING SIMULATION APPROACH

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ABSTRACT: Simulation has become an indispensable tool which enables engineers, designers, planner and managers, to study, analyze and evaluate complex situations that would not be otherwise possible. In this paper, a job shop simulation model with stochastic variables and constraints in a high precision component manufacturer is presented. Data was collected from the manufacturer of high-mix and low volume products, each product with different processing specifications. A discrete event simulation model was developed using the Witness Simulation software. The model is then verified and validated with the data from the company. Simulation experiments were conducted to identify bottlenecks in the manufacturing system and to test several scenarios of operators' overtime. The experiments also have the ability to estimate the completion date for customer orders. Results show that simulation model gives better estimates of the completion dates of the customer orders compared to the production planner of the company.

KEYWORDS: *Simulation, Job Shop, Bottlenecks, Witness, Manufacturing Completion Dates.*

1.0 INTRODUCTION

The manufacturing industry is under intense pressure from the increasingly competitive global marketplace. trends of lower product costs, shorter processing time, and more product variety had resulted in a more challenging manufacturing environment [1]. With a simulation model, a manager can try out the several policy decisions within a short time frame. Simulation is also a powerful tool to help sort through cause-and-effect relationships and gain a better understanding of what is actually causing a particular problem in the system [2]. A great deal of research works has been conducted on deterministic scheduling and control of job shop production systems in the last three decades, only very few researches have considered controlling such a system with stochastic parameters [3]. This flexibility makes job shop problems strongly Np-hard [4], [5] and [6]. Analysis of job shop systems is more complex than traditional ones because of both stochastic and flexible nature of the manufacturing system [7], [8] and [9]. Most of the researches simulate the job shop model start with empty system, but the author preload the orders in the simulation model. This study is conducted in a high precision components manufacturer located in Melaka industrial zone. The company produces high-mix and low-volume customized products, each product with different specifications (machine routes). Currently the planner of the company plans the production using the manual approach. Due to this inaccurate approach, the company encountered difficulty in meeting the due date of customers' orders. Apart from late deliveries, the management is also concerned on the inaccurate computation of the cycle times and product throughputs. The overall machine configuration in the company is a pure job shop environment, characterized by the fact the machine layouts are fixed but the processing routes not necessary the same for each job. in such configurations, the job has to visit certain machines and not necessary every machine. Identifying bottleneck and completion dates for customer orders in such a complex environment can constitute a real challenge to planners and production managers.

2.0 METHODOLOGY

A discrete-event simulation baseline model of the company is developed using the Witness simulation software. The model is verified and validated with the data from the company. This model reflects the complexity of the real manufacturing system which includes the jobs, machines, work in progress (WIP), technicians, and all main elements and attributes in the job shop. The machines include milling, turning, CNC milling, EDM, grinding carbide, wire cut, cylindrical grinding, laser marking, super drills, deburring station, sand blasting and internal heat treatment. The model simulates a total of 816 jobs, in which each job undergoes different process route. In addition, the cycle time for each process differs for each job. The objective of the research is to develop a decision support to assist the manager to estimate the delivery date of the customer orders and the man power requirements to support the orders. Two experiments have been carried out by using the simulation model. The objective of the Experiment 1 is to achieve the minimum targeted demand by reducing the waiting time and managing the utilization at the identified bottlenecks. This is achieving by changing the overtime and shift pattern of the technicians. Experiment 2 is to improve the accuracy of the determination of customer orders due dates

3.0 SIMULATION MODEL EXPERIMENTATION

3.1 DESIGN OF EXPERIMENT 1

Based on the results generated from the simulation run of existing system, mean total output per month for the existing system was 338 jobs, the highest mean waiting time in the buffer was at the wire cut workstation (24050.00 minutes) and the highest mean utilization of machines and technicians was at the milling workstation (93.65% and 97.75%) respectively. Therefore, the base model showed that the existing system had two bottleneck candidates, wire cut workstation with highest waiting time in buffer and milling workstation with highest utilization of machine and technicians. Thus, efforts need to be taken to address this problem to meet customer demand. The flow chart is given in Figure 1 with the procedure as described below.

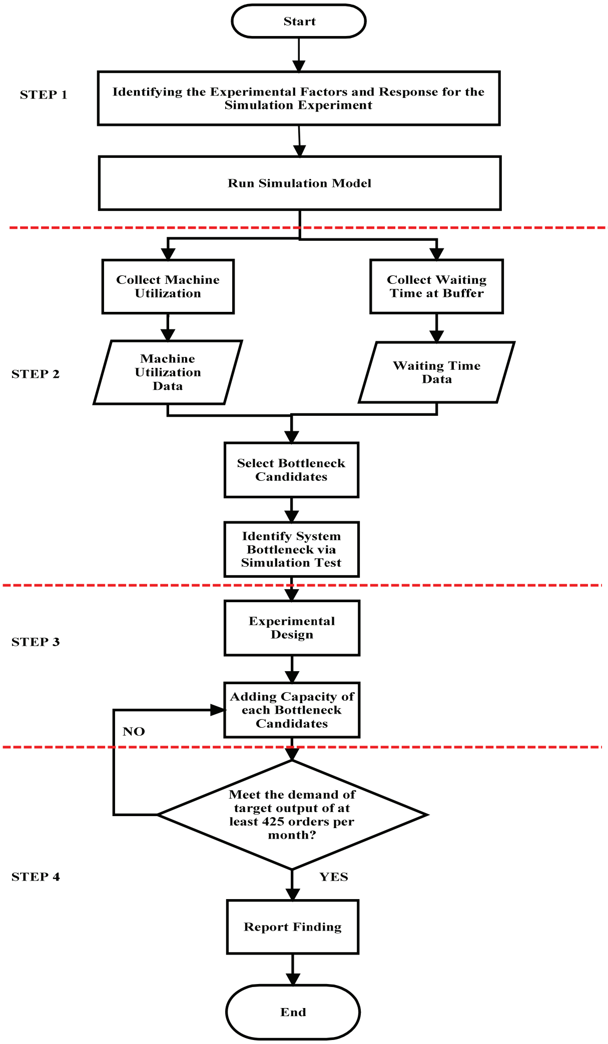


Figure 1: Overall system to achieve the minimum targeted demand by reducing the waiting time and managing the utilization at the identified bottlenecks

Step 1: Identifying the Experimental Factors and Responses for the Simulation Experiment

The experimental factors for the simulation experiment are the overtime and shift pattern for the technicians, mean machining time and process routes for the customer orders while the responses are mean total utilization of the machines, mean total utilization of the technicians, mean total waiting time in buffer, and mean total output of the simulation system.

Step 2: Bottleneck Identification

The simulation is run for existing system to collect statistics of the following key performance indicators; (1) utilization of the machine and (2) waiting time at each buffer. To identify the bottleneck candidates, two factors are required, machine utilization and the waiting time at each buffer. Considering each factor:

(1) Machine utilization: The machines that have high utilization are selected to be the bottleneck candidates
(2) Waiting time at each buffer: The buffer that have longest waiting time are selected to be the bottleneck

Several bottleneck candidates can be identified from the utilization statistics and waiting time at each buffer from the simulation run.

Step 3: Developing the test by Adding Capacity of Each Bottleneck Candidate

In the experiment, 64 tests were created by adding the capacity of each bottleneck candidates by changing the overtime and shift pattern for the technicians (Wire cut and milling workstation are identified as bottleneck candidates). According to the policy of the case company, maximum working time for the technician is 12 hours per day. Thus, maximum overtime for the technician on weekday is 4 hours. Table 1 shows the detail for the 64 tests. In test 1-16, overtime (of 1 to 4 hours) were added for wire cut technicians (for Shift 1) and for the milling technicians. In test 17-32, overtime (of 1 to 4 hours) were added for wire cut technicians (for Shift 2) and milling technicians. Test 33-60 are about combination between overtime (of 1 to 4 hours) for wire cut technicians Shift 1 and Shift 2 and also milling technicians. Test 61-64 change the shift pattern for wire cut technicians and apply overtime (of 1 to 4 hours) for milling technicians. 4 replications of simulation runs are needed for each test.

Step 4: Comparing the Mean Output with the Target Output

The target output which is given by the production planner of the case company is at least 425 jobs per month. The mean of output obtained from the simulation test was compared with the target output. If the results yield an output that exceeded the demand, then the process will stopped. Otherwise, return to step 3. The total mean output improvement is determined by using Equation 1, the total mean work in progress reduction is calculated by using Equation 2 and the total mean waiting time in buffer reductions is obtained by using Equation 3 as shown below. Result will be discussed in next section.

$$\boldsymbol{TMOI_i = \left(\frac{(TMO_i\_ETMO)}{ETMO}\right)100} \tag{1}$$

Where,

$\boldsymbol{i}$ = 1, 2……31 (test number)

$\boldsymbol{TMOI_i}$ = Total mean output improvement (%)

$\boldsymbol{ETMO}$ = Existing total mean output (job)

$\boldsymbol{TMO_i}$ = Total mean output (job)

$$\boldsymbol{TMWIPR_i = \left(\frac{(TMWIP_i - ETMWIP)}{ETMWIP}\right)100} \tag{2}$$

Where,

$\boldsymbol{i}$ = 1, 2……31 (test number)

$\boldsymbol{TMWIPR_i}$ = Total mean work in progress reduction (%)

$\boldsymbol{TMWIP_i}$ = Total mean work in progress (job)

$\boldsymbol{ETMWIP}$ = Existing total mean work in progress (job)

$$\boldsymbol{TMWTR_i = \left(\frac{(TMWI_i - EMWT)}{EMWT}\right)100} \tag{3}$$

Where,

$\boldsymbol{i}$ = 1, 2……31 (test number)

$\boldsymbol{TMWTR_i}$ = Total mean waiting time reduction (%)

$\boldsymbol{TMWT_i}$ = Total mean waiting time (minute)

$\boldsymbol{EMWT}$ = Existing mean waiting time (minute)

3.2 Design Of Experiment 2

The objective of the experiment 2 is to improve the due date' prediction of the customer orders by using the developed simulation model. Figure 2 shows the procedure to run the Experiment 2 with the steps as described.

Step 1: Identifying the Experimental Factors and Response for the Simulation Experiment

The experimental factors for the simulation experiment are the mean machining times and process routes for the customer orders while the response is the mean due dates of the customer order.

Step 2: Data Collection for Mean Due Dates from the Simulation Model

The actual completion dates and due dates predicted by planner are given by the company. The simulation is run for existing system to collect the mean due dates of 35 customer orders. 4 replications of simulation runs are needed.

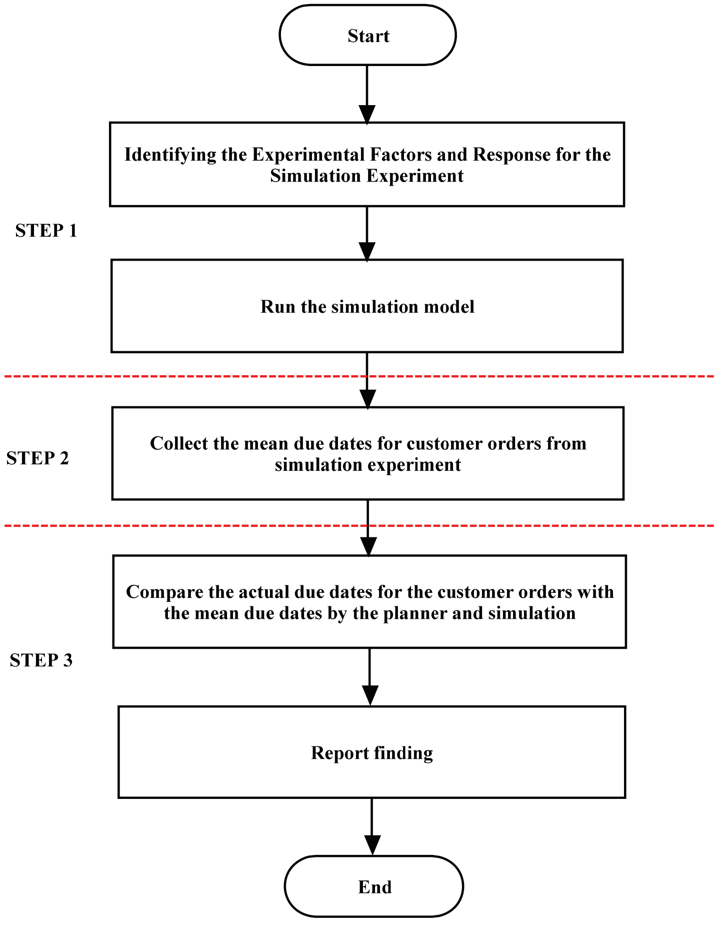


Figure 2: Overall system to improve the due dates' determination of the customer orders

Step 3: Comparing the Actual Completion Dates with Due Dates Predicted by the Planner and Actual Completion Dates with Mean Due Dates by Simulation Model

Compare the actual completion dates and due dates predicted by the planner for the customer orders. After collecting the mean due dates from the simulation model, compare the actual completion dates with the results from simulation model.

Table 1: Table of test

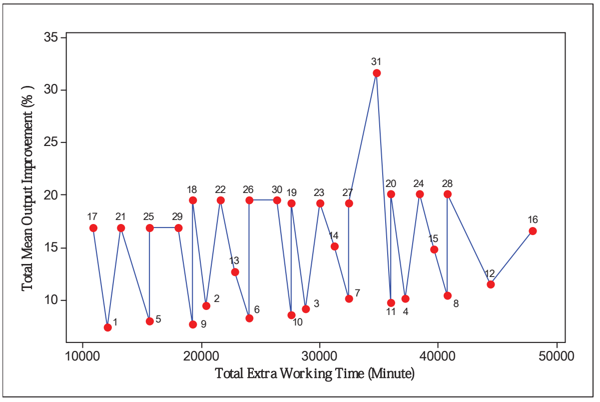
Test	Overtime for Wire Cut Technicians (Shift 1)				Overtime for Wire Cut Technicians (Shift 2)				Overtime for Milling Technicians			
	1	2	3	4	1	2	3	4	1	2	3	4
1	✓								✓			
2	✓									✓		
3	✓										✓	
4	✓											✓
5		✓							✓			
6		✓								✓		
7		✓									✓	
8		✓										✓
9			✓						✓			
10			✓							✓		
11			✓								✓	
12			✓									✓
13				✓					✓			
14				✓						✓		
15				✓							✓	
16				✓								✓
17					✓				✓			
18					✓					✓		
19					✓						✓	
20					✓							✓
21						✓			✓			
22						✓				✓		
23						✓					✓	
24						✓						✓
25							✓		✓			
26							✓			✓		
27							✓				✓	
28							✓					✓
29								✓	✓			
30								✓		✓		
31								✓			✓	
32								✓				✓
33	✓				✓				✓			
34	✓				✓					✓		
35	✓				✓						✓	
36	✓				✓							✓
37		✓				✓			✓			
38		✓				✓				✓		
39		✓				✓					✓	
40		✓				✓						✓
41			✓				✓		✓			
42			✓				✓			✓		
43			✓				✓				✓	
44			✓				✓					✓
45				✓				✓	✓			
46				✓				✓		✓		
47				✓				✓			✓	
48				✓				✓				✓
49	✓					✓				✓		
50	✓						✓				✓	
51	✓							✓				✓
52		✓			✓				✓			
53		✓					✓				✓	
54		✓						✓				✓
55			✓		✓				✓			
56			✓			✓				✓		
57			✓					✓				✓
58				✓	✓				✓			
59				✓		✓				✓		
60				✓			✓				✓	
61		✓										
62			✓									
63				✓								
64					✓							

4.1 Results and Discussions for Experiment 1

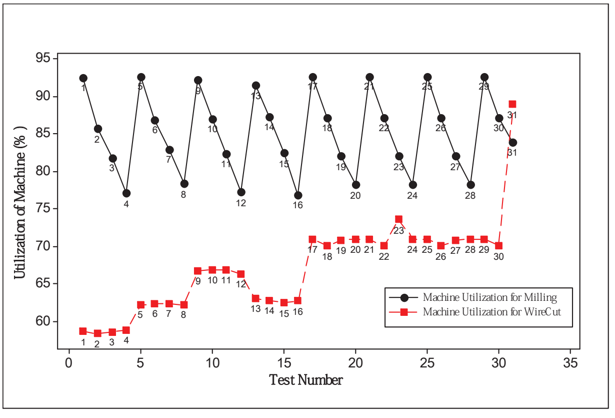
The objective of this experiment is to achieve a targeted demand by reducing the waiting time and managing the utilization at the identified bottlenecks. After running the simulation models for all the proposed alternatives, the results obtained are summarized in Table 2. Each data in the tables is the mean of the 4 replications of each of the 31 test. After running the simulation model for all proposed shift patterns and overtimes, the results for each alternative can be compared and the best alternative selected.

Monthly salary for a technician is RM800 for 20 working days in a month. Thus, the rate of the overtime per hour is RM7.50 (RM5/hour x 1.5). The alternative for adding 4 hours overtime at all milling and wire cut Shift 2 technicians (refer to Test 31 in Table 2) with RM4350 yields the highest improvement in the total mean output of 31.7%. On the other hand, by adding 1 hour overtime at all milling and wire cut Shift 1 technicians (refer to Test 1 in Table 2) with RM1500 results the lowest result as 7.4%. The complete results are presented in Table 2. First column of Table 2 shows the test number. Extra working time at wire cut and milling workstation are shown in columns 2, 3 and 4. Column 5 shows the total extra working time for both workstations by adding all the value in columns 2, 3 and 4. Total mean output is shown in column 6 and the percentage of improvement for the total mean output is shown in column 7. Column 8 shows the additional cost for the extra time.

Figure 3 shows the results of total mean output improvement versus working time at milling and wire cut workstation. The labels in graph show the test number, i. The graph shows that additional working time at milling and wire cut workstation is not directly proportional to the total mean output improvement. This means that total mean output improvement will not necessarily increase when the additional total working time increases. This could be due to other constraints such as limited capacities at other workstations. The alternative of adding 1 hours overtime at all milling technicians and wire cut technician Shift 2 (Test 17 with 10800 minutes total extra working time) yields the better result in the total mean output improvement than adding 4 hours overtime at all milling technicians and wire cut technician Shift 1 (Test 16 with 48000 minutes total extra working time) .The lowest total mean output improvement is 7.4% by adding 1 hour overtime at all milling technicians and wire cut Shift 1 technicians (Test 1 with 12000 minutes total extra working time). Figure 3 indicates that the alternative of adding 4 hours overtime at all wire cut technicians Shift 2 and milling technicians (Test 31 with 34800 minutes total extra working time) can yield the highest improvement for total mean output, 31.7%. This maybe because of the utilization for both machine (Milling and Wire Cut) is exceeds 80% i n Test 31 (Refer to Figure 4). The system in the case company is stochastic because each job has different arrival time, quantity, process route and processing time. Thus, Figure 3 is useful for the manager or planner to assign the extra working time on the technicians in order to achieve the demand.



(Note: the figure in the graph represents the test number)
Figure 3: Total mean output improvement versus total extra working time at milling and wire cut workstation

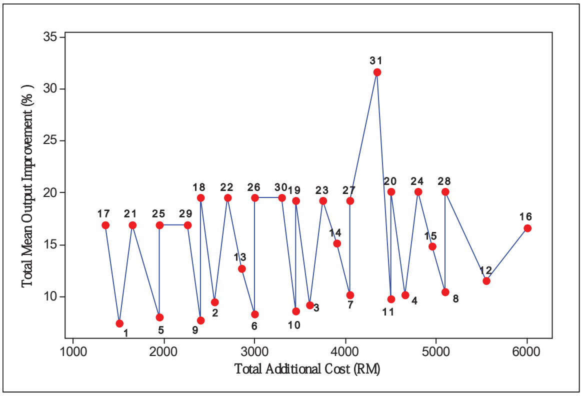


(Note: the figure in the graph represents the test number)
Figure 4: Total mean machine utilization for milling and wire cut machine after adjustment of working time

Figure 4 shows the graph of total mean output improvement (%) versus total additional overtime cost (RM). The labels in graph show the test number, i. Figure 5 indicates by adding total additional cost of RM4350 per month (Test 31) can yields the highest improvement for total mean output, 31.7%. On the other hand, by adding total additional cost of RM1350 per month (Test 17) obtains better improvement for the total mean output, 16.9% than adding total additional cost of RM6000 per month (Test 16). Figure 5 shows by adding total additional cost of RM4500 (Test 20), RM4800 (Test 24) and RM5100 (Test 28) per month result in the same improvement for the total mean output as 20.1%. Besides, by adding additional cost of RM2400 (Test 18), RM2700 (Test 22), RM3000 (Test 26), and RM3300 (Test 30) per month obtain the same improvement for the total mean output as 19.5%. By adding total additional cost of RM3450 (Test 19), RM3750 (Test 23) and RM4050 (Test 27) per month has the same improvement for the total mean output as 19.2%. Furthermore, by adding total additional cost of RM1350 (Test 17), RM1650 (Test 21), RM1950 (Test 25), and RM2250 (Test 29) per month yields the same improvement for the total mean output as 16.9%. Total mean output improvement as 10.1% obtained by adding additional cost of RM4050 (Test 7) and RM4650 (Test 4) per month. From Figure 5, the result shows that total mean output does not certainly increase by spending more overtime cost.

Table 2: Result of the total mean manufacturing cycle time and additional cost after the adjustment of the extra working time

Test, i	Extra Working Time at Wire Cut, Shift 1 (minutes), $EWTWC1_i$	Extra Working Time at Wire Cut, Shift 2 (minutes), $EWTWC2_i$	Extra Working Time at Milling (minutes), $EWTM_i$	Total Extra Working Time (minutes), $TEWT_i$	Total Mean Output (jobs), TMO_i	Total Mean Output Improvement (%), $TMOI_i$	Total Additional Cost (RM), TAC_i
1	3600	0	8400	12000	363	7.4	1500
2	3600	0	16800	20400	370	9.5	2550
3	3600	0	25200	28800	369	9.2	3600
4	3600	0	33600	37200	372	10.1	4650
5	7200	0	8400	15600	365	8.0	1950
6	7200	0	16800	24000	366	8.3	3000
7	7200	0	25200	32400	372	10.1	4050
8	7200	0	33600	40800	373	10.4	5100
9	10800	0	8400	19200	364	7.7	2400
10	10800	0	16800	27600	367	8.6	3450
11	10800	0	25200	36000	371	9.8	4500
12	10800	0	33600	44400	377	11.5	5550
13	14400	0	8400	22800	381	12.7	2850
14	14400	0	16800	31200	389	15.1	3900
15	14400	0	25200	39600	388	14.8	4950
16	14400	0	33600	48000	394	16.6	6000
17	0	2400	8400	10800	395	16.9	1350
18	0	2400	16800	19200	404	19.5	2400
19	0	2400	25200	27600	403	19.2	3450
20	0	2400	33600	36000	406	20.1	4500
21	0	4800	8400	13200	395	16.9	1650
22	0	4800	16800	21600	404	19.5	2700
23	0	4800	25200	30000	403	19.2	3750
24	0	4800	33600	38400	406	20.1	4800
25	0	7200	8400	15600	395	16.9	1950
26	0	7200	16800	24000	404	19.5	3000
27	0	7200	25200	32400	403	19.2	4050
28	0	7200	33600	40800	406	20.1	5100
29	0	9600	8400	18000	395	16.9	2250
30	0	9600	16800	26400	404	19.5	3300
31	0	9600	25200	34800	445	31.7	4350



(Note: the figure in the graph represents the test number)
Figure 5: Total mean output improvement versus total additional cost

4.2 Results and Discussions for Experiment 2

The objective of Experiment 2 is to improve the due date' prediction of the customer orders by using simulation model. Table 3 compares the actual completion dates with the due dates predicted by the planner and the mean due dates by simulation model. The actual completion dates and the due dates predicted by planner were given by the company while the mean due dates by simulation are obtained from Experiment 2. Column 1 in Table 3 shows the customer orders, column 2 shows the actual completion dates, column 3 shows the due dates by planner and column 4 shows the mean due dates by simulation model. Differences between actual completion dates with the due dates by planner are show in column 5 while differences between actual completion dates with the mean due dates by simulation model are show in column 6.

The negative sign in column 5 and 6 indicates the due dates by the planner or simulation model are later than the actual completion dates. Out of 35 customer orders, the planner of the company only performs better than simulation model in 5 instances. This shows that the prediction from the simulation model is 85.7% accurate. The planners of the company predict the complete date of the customer order based on their experiences about the machining times for each process and assign a tolerance for the machining times. The inaccuracy of the prediction by the planner maybe due to the fact that They did not include the waiting times of the customer order in each buffer before workstation because is not feasible to calculate the waiting times for each customer orders with the mathematical modelling. Secondly, is not practical for the planners to determine the current capacity and condition of the production flow because the arrival times and machining times are stochastic.

Table 3: Comparison between actual completion dates (ACD) with due dates by the planner (DDP) and ACD with mean due dates by simulation (MDDS)

Customer Order	Actual completion dates, *ACD*	Due dates by the Planner, *DDP*	Mean Due Dates by Simulation Model, *MDDS*	Differences Between ACD with DDP (Day) $(ACD - DDP)$	Differences Between ACD with MDDS (Day) $(ACD - MDDS)$	Which approach performs better?
Order A1	22/6/2010	4/6/2010	6/6/2010	18	16	MDDS
Order A2	16/6/2010	4/6/2010	30/5/2010	12	17	DDP
Order A3	19/7/2010	2/7/2010	12/6/2010	17	37	DDP
Order A4	3/6/2010	17/5/2010	20/5/2010	17	14	MDDS
Order A5	2/6/2010	17/5/2010	6/6/2010	16	-4	MDDS
Order A6	31/5/2010	17/5/2010	12/6/2010	14	-12	MDDS
Order A7	31/5/2010	17/5/2010	8/5/2010	14	23	DDP
Order A8	31/5/2010	17/5/2010	31/5/2010	14	0	MDDS
Order A9	3/6/2010	4/6/2010	3/6/2010	-1	0	MDDS
Order A10	10/6/2010	7/5/2010	11/6/2010	34	-1	MDDS
Order A11	1/6/2010	18/5/2010	30/5/2010	14	2	MDDS
Order A12	31/5/2010	18/5/2010	30/5/2010	13	1	MDDS
Order A13	18/6/2010	18/5/2010	13/6/2010	31	5	MDDS
Order A14	10/6/2010	19/5/2010	12/6/2010	22	-2	MDDS
Order A15	10/6/2010	19/5/2010	12/6/2010	22	-2	MDDS
Order A16	31/5/2010	7/6/2010	8/6/2010	-7	-8	DDP
Order A17	18/6/2010	7/6/2010	16/6/2010	11	2	MDDS
Order A18	30/6/2010	7/6/2010	22/6/2010	23	8	MDDS
Order A19	28/6/2010	20/5/2010	19/6/2010	39	9	MDDS
Order A20	23/6/2010	20/5/2010	13/6/2010	34	10	MDDS
Order A21	21/6/2010	20/5/2010	14/6/2010	32	7	MDDS
Order A22	21/6/2010	20/5/2010	30/5/2010	32	22	MDDS
Order A23	22/6/2010	20/5/2010	12/6/2010	33	10	MDDS
Order A24	7/6/2010	21/5/2010	13/6/2010	17	-6	MDDS
Order A25	1/6/2010	21/5/2010	25/5/2010	11	7	MDDS
Order A26	7/6/2010	21/5/2010	25/5/2010	17	13	MDDS
Order A27	15/6/2010	21/5/2010	12/6/2010	25	3	MDDS
Order A28	21/6/2010	7/6/2010	13/6/2010	14	8	MDDS
Order A29	17/6/2010	7/6/2010	18/6/2010	10	-1	MDDS
Order A30	14/6/2010	7/6/2010	14/6/2010	7	0	MDDS
Order A31	18/6/2010	7/6/2010	19/6/2010	11	-1	MDDS
Order A32	18/6/2010	9/6/2010	13/6/2010	9	5	MDDS
Order A33	18/6/2010	9/6/2010	13/6/2010	9	5	MDDS
Order A34	2/6/2010	21/5/2010	3/6/2010	12	-1	MDDS
Order A35	29/5/2010	21/5/2010	9/6/2010	8	-11	DDP

5.0 CONCLUSION

From Experiment 1, the results indicated that the alternative of adding 4 hours overtime at all wire cut technicians Shift 2 and milling technicians (Test 31 with 34800 minutes total extra working time) with total additional cost of RM4350 per month can yield the highest improvement for total mean output, 31.7%. The simulation model can be used to plan for the extra working time on the technicians based on the financial constraint.

The results from Experiment 2 show that out of 35 customer orders, planner of the company only performs better than simulation model on 5 orders while the simulation performs better than the planner on 31 orders which accuracy of the simulation model on due dates' prediction is 85.7%. By using the simulation model in Experiment 2, the planners can understand the capacity and the condition of the production flow because the simulation model simulates all the customer orders. In addition, the waiting times also included in the simulation model other than machining times.

The two experiments achieve the objectives and the simulation model was able to provide required output. The simulation model can be used to identify the man power requirement to achieve the demand by identifying the bottleneck candidates and to improve the accuracy of the determination of customer orders due dates. Simulation models have the advantage of being able to provide greater detail and take into account the intrinsic variation of a dynamic job shop system. Without the flexibility of a computer simulation model, the number of combinations and testing variations required by the two experiments would be extremely time consuming and costly.

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