

A simulation study of capacity utilization to predict future capacity for manufacturing system sustainability

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Abstract. Capacity utilization (CU) measurement is an important task in a manufacturing system, especially in make-to-order (MTO) type manufacturing system with product customization, in predicting capacity to meet future demand. A stochastic discrete-event simulation is developed using ARENA software to determine CU and capacity gap (CG) in short run production function. This study focused on machinery breakdown and product defective rate as random variables in the simulation. The study found that the manufacturing system run in 68.01% CU and 31.99% CG. It is revealed that machinery breakdown and product defective rate have a direct relationship with CU. By improving product defective rate into zero defect, manufacturing system can improve CU up to 73.56% and CG decrease to 26.44%. While improving machinery breakdown into zero breakdowns will improve CU up to 93.99% and the CG decrease to 6.01%. This study helps operation level to study CU using “what-if” analysis in order to meet future demand in more practical and easier method by using simulation approach. Further study is recommended by including other random variables that affect CU to make the simulation closer with the real-life situation for a better decision.

Keywords: capacity utilization, capacity gap, simulation, machinery breakdown, product defective rate

1. Introduction

Capacity is critically important for a manufacturing system. A manufacturing system that fails to manage its resources, to ensure that capacity is available and is being used efficiently, risks losing its competitive advantage. A good capacity planning and management are required to ensure a manufacturing system meets the demand. A good capacity planning enables the manufacturer to gain revenue in the future demand uncertainty [1]. Furthermore, better capacity management is the key to reduce cost [2] and manufacturing system sustainability [3].

Capacity is described as the level of output that can be achieved by a manufacturing system in a given period of time under normal working condition. Many of manufacturers ignore the measurement of capacity and assuming their resources have enough capacity. However, in many cases, the capacity utilization (CU) is far below optimum [4]. CU is an important factor in measuring manufacturing system performance and indicates whether or not a manufacturing system can support future demand without further investment.



CU is determined by machinery factors such as processing time, machinery set-up time, yield and downtime [5]. Some of past research found that productivity and performance of manufacturing system are highly depended on machinery utilization [3]. Therefore, measuring CU is strongly associated with measuring machinery utilization. In general, machinery utilization is defined as ratio actual output to design capacity. Design capacity is referring to engineering concept of capacity, which is the theoretical maximum output of a machinery in a given period under ideal conditions.

It is evident that machinery utilization is linked with machinery availability, performance, and quality. Previous research reported that machinery breakdown, set-up, and product defects are the daily major issues faced by the manufacturer that affected productivity and capacity of a manufacturing system [6]. Machinery breakdown is the most significant contributor and the root cause of utilization loss in manufacturing system [7,8]. The problem is, the occurrences of breakdown are uncertain and random following certain probability distribution [9]. Consequently, it is necessary to examine the effect of machinery breakdown on the capacity of the manufacturing system.

The second biggest contributor and the root cause of utilization loss in the manufacturing system are product defects. Product defects are taken into account of utilization loss, which accounts for producing pieces that do not meet quality standards, including pieces that require rework which reduce overall capacity. In the same manner with breakdown, product defects also occur uncertainly and randomly following a certain probability distribution.

Past literature has concentrated on developing a mathematical model on CU measurement by looking at inputs-outputs as deterministic variables. For example, Kumru [4] developed a mathematical to determining the capacity and its level of utilization for single-machine multiple-product case by considering processing time, set-up time, product defective rate and maintenance downtime as deterministic variables. However, the results overlook that product defects and machinery breakdown happened uncertainly and randomly following a certain probability distribution in a manufacturing system.

Stochastic simulation is the most suitable tool to analyze a system with uncertainty in the form of random variables with certain probability distributions [10]. Simulation is low cost, secure and fast, yet a powerful analysis tool in obtaining the performance measures of a system. Simulation has been used widely to study a manufacturing system with stochastic variables.

The main objective of this study is to predict the future capacity of a manufacturing system by using simulation approach. The probability distribution of machinery breakdown and product defective rate will be identified as random variables of machinery utilization. Simulation, being “what if” experiment, will be a useful technique to study the effects of capacity changes if the variables such as breakdown and or product defects changes. A case study is conducted as a model of the real manufacturing system and ARENA simulation software is used as the platform to do virtual experiments.

2. Capacity utilization

The commonly used definition of CU is the ratio of actual output (Q_A) to the potential output (Q_P) of a machinery. The potential output in this definition refers to the capacity of a machinery. Associated with this potential output, utilization could be measured from two perspectives, which are engineering and economic perspective.

In the economic perspective, CU is measured based on the ratio of actual economic output and potential economic output. This means that all output must be translated in the cost function. This method largely depends upon the level of availability of economic data. If detailed costs and earnings information are available beyond an index of output per time, it may be possible to measure economic perspective of CU [5]. However, the result of this type of CU is not useful at factory level for evaluating performance and making operating policy [3].

In most cases, data are known only on: physical input levels, operation characteristics, and output levels. For that reason, engineering perspective of CU is more practical. In engineering perspective,

CU is measured based on actual physical output units and potential physical output units. The mathematical expression for engineering perspective of CU is shown in expression (1) below:

$$\text{Capacity utilization (CU)} = \frac{\text{Actual Output (Q}_A\text{)}}{\text{Potential Output (Q}_P\text{)}} \quad (1)$$

3. Capacity gap

Unutilized or unused capacity which not produce products appears as CG. In operational term, this CG is called as production or output gap. In the mathematic analysis, CG is calculated as the difference between the potential output (Q_P) and actual output (Q_A) and usually stated in percentage as shown in mathematical expression (2) below:

$$\text{Capacity gap (CG)} = \frac{\text{Potential output (Q}_P\text{)} - \text{Actual output (Q}_A\text{)}}{\text{Potential Output (Q}_P\text{)}} \times 100\% \quad (2)$$

CG is recognized as non-value added inputs and generally contributes to reducing the performance of machinery. The goal of a manufacturing system is to maximize CU and simultaneously minimize the CG. However, previous research found that many manufacturing systems run far from it potential output. In previous research in a garment firm, Lee and Shahidul [4] found that the machinery runs 67.3% of CU only. Another studied by Shahidul et. al. [3] revealed that manufacturing system run at 70% of CU.

Product processing time and set-up time of machinery, product defective rate, and machinery downtime are the determinants of CU and CG [5]. Optimization of production cycle time has a link with maximizing CU and minimization of the CG. On the other hand, in order to optimize CU, set-up time of machinery, product defective rate and machinery breakdown should be minimized. Therefore, in this perspective machinery factor inputs are more concerned.

4. Manufacturing system model

The manufacturing firm being studied is a make-to-order (MTO) type, which means the manufacturing firm only run production in response to customers' orders and do not keep finish good in stock. The firm has to supply a wide variety of products, ranging from a set of standard ones to all orders requiring a customized one. The degree of product customization; which covers pure customization, tailored customization, standard customization and non-customization, and the amount of product variety diversify are high. Each potential order from the inquiry tends to be for a differing number of units and requires varying routings and processing times through the production facilities.

The products produced by manufacturing firm studied are glass products for building, decoration and safety. The main types of the glass are tempered glass, laminated glass, insulated glass/double glazing glass and decorative coated glass/ceramic printing glass. The customer could customize the glass type ordered, for example, tempered + laminated glass, tempered + insulated glass, insulated + ceramic printing glass, etc. in a specific dimension.

The first process is glass cut into customer's specification, continued with edge work to remove sharp edge. Some products need to be drilled for installation purposes regarding customer's order. Before going to main processes, the glass goes for washing process. The main processes will follow customer's requirement. Heat soak treatment is done after the main processes, served as destruction test. In this, stage the finished product will be heated until certain temperature for some period of time.

If the product fails in the test, the product will be crack or broken. The pass product will be packed and ready to ship to the customer.

In this study, short-run production function and engineering concept of CU is used to develop a proposed method. A simulation model of the manufacturing system is developed using ARENA software.

4.1 Data collection

In order to study the manufacturing system, data collection is conducted as follows:

1. All customers' order data from January 2016 to December 2016 were analyzed; product type, quantity, and order date were collected. A family product was developed based on process routing similarity.
2. All processes required to make the product were analyzed; resources, material, and process time were identified and documented.
3. All production data were collected; machinery breakdown, product defective rate and actual output were verified and validated.

4.2 Analysis of probability distribution

The probability distribution is a critical parameter in this study as an input to the simulation. The probability is analyzed from 1-year data using Input Analyzer of ARENA Software. The data analyzed to get the best distribution probability were time between machine failures, time to repair and product defective rate. The analysis result shown in **Table 1**.

Table 1. Probability distribution of time between machine failures, time to repair and defective rate by machine type

Machine name	Time to machine failure		Time to repair		Defective Rate	
	Expression	Square error	Expression	Square error	Expression	Square error
Cutting machine	70 + EXPO(92.9)	0.034744	20 + EXPO(3.16e+003)	0.008453	-	-
Tempered machine	-0.001 + EXPO(36.7)	0.095347	20 + EXPO(3.39e+003)	0.037840	UNIF(84, 100)	0.091667
Laminating machine	UNIF(45, 520)	0.050000	-0.001 + EXPO(2.36e+003)	0.020933	TRIA(84, 98.4, 100)	0.129938
Insulating machine	-0.001 + EXPO(70.7)	0.003711	UNIF(2.4e+003, 2.24e+004)	0.039669	NORM(99.6, 0.814)	0.252264
Ceramic printing machine	-0.001 + EXPO(28.8)	0.034964	510 + EXPO(1.03e+004)	0.091538	NORM(97.9, 3.38)	0.212384
Heat soak machine	-0.001 + EXPO(20)	0.063972	45 + EXPO(225)	0.065741	TRIA(90, 99, 100)	0.304012

4.3 Model conceptualization

The simulation model started with the arrival of customers' order by family product following its probability distribution respectively. The entities in this simulation are the product families which flow in production facilities follow the customer's order. The SEQUENCE module is used to model the process flow base on the family product type. The ROUTE module is used to move the entities from one station to another station, but the transportation time was excluded in this study.

4.4 Model construction

The model then is constructed using ARENA simulation software as shown in **Figure 1**.

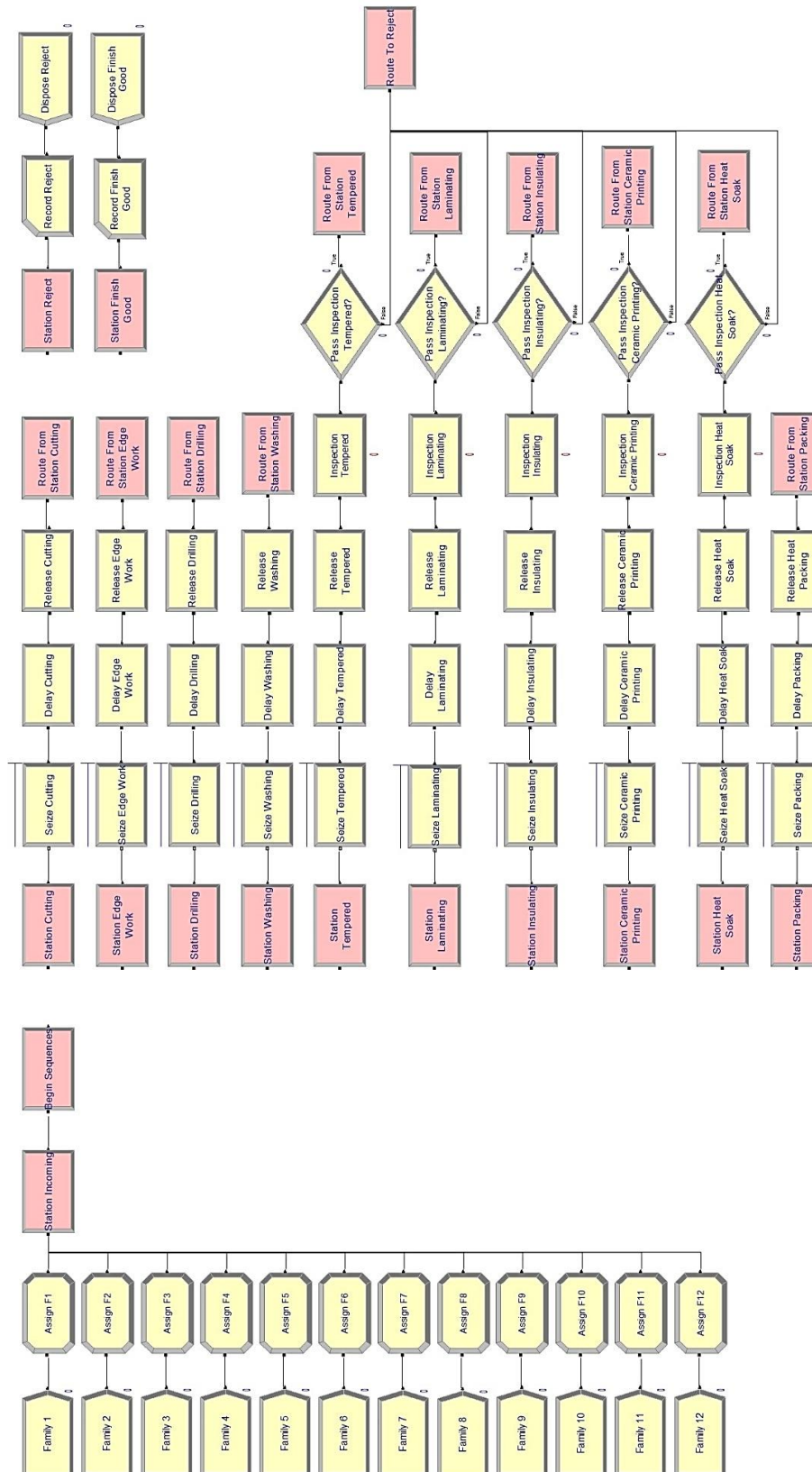


Fig. 1. ARENA simulation model

4.5 Verification and validation

To ensure the model is correct and accurate, verification and validation are implemented. Verification is done by comparing the model logic with the product routings. The animation was used to verify the movement of each family product follows the sequence like in the real production. For this simulation, twelve entities are entering the system according to sequences. Therefore, it indicates that this simulation modeling is worked and verified.

Validation is performed by a trial run by using customers' order in week 4 of the year 2016 as input, then comparing the output result of the trial run with actual production output. For the trial run, ten replication were performed to calculate bias and Confidence-Interval Estimation.

The average output of trial run is 3139 with standard deviation 130.5842 while the actual output in week 4 of the year 2016 was 3110. The average bias is 111.6 or around 4% from actual output. Taking 95% Confidence Level, the confidence interval estimation is:

$$3110 \pm t_{0.05/2, 10-1}(130.5842) \sqrt{1 + \frac{1}{10}} = 3110 \pm 309.80 \text{ or } 3110 \pm 10\%, \text{ which is pretty valid.}$$

5. Simulation Result

The simulation results in this study are focused on two main performance measures, which are production output and machinery utilization. The simulation will run for 52 replications represent number of weeks in a year. The first simulation was run to analyze machine up time and production yield. The time between failure probability distribution and time to repair probability distribution were used as input to model machinery up time. **Figure 2** shows machinery up time from the simulation result. While product defective rate probability distribution was used as input to model production yield. **Figure 3** shows production yield from the simulation result.

It is found that the lowest uptime is for laminating machine, with average 88.69% uptime, while heat soak machine had the highest uptime, which is 97.85% in average. The same result was found for production yield, the laminating machine had the lowest production yield with 91.20% in average and the heat soak machine had the highest production yield with 98.79% in average. Both machineries uptime and production yield affected overall CU and CG.

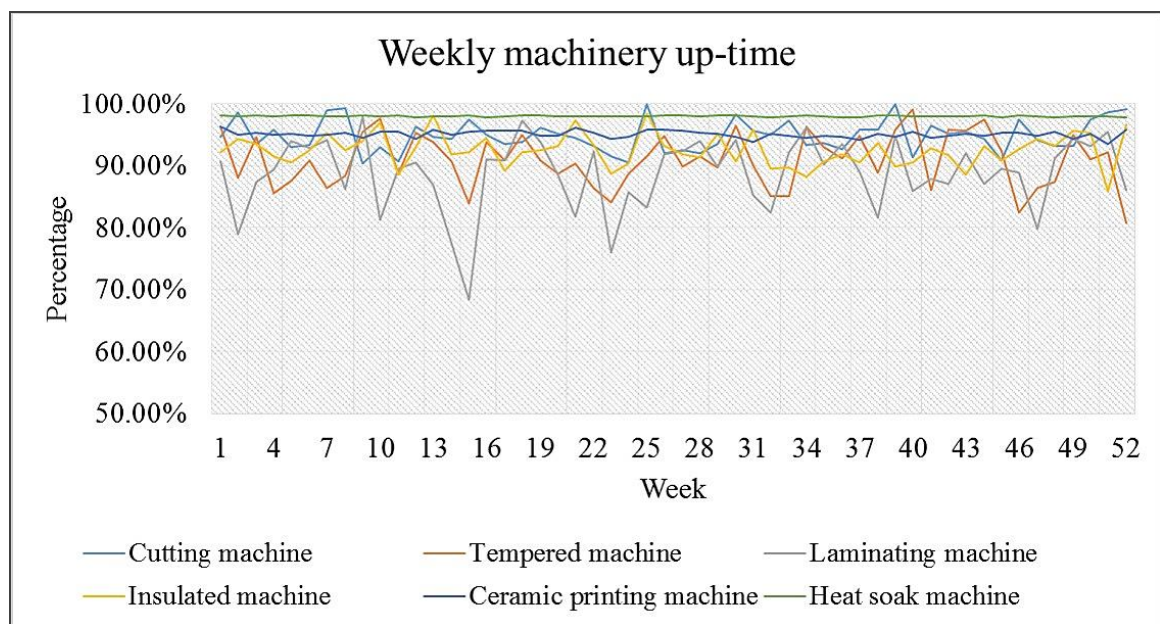


Figure 2. Weekly machinery uptime

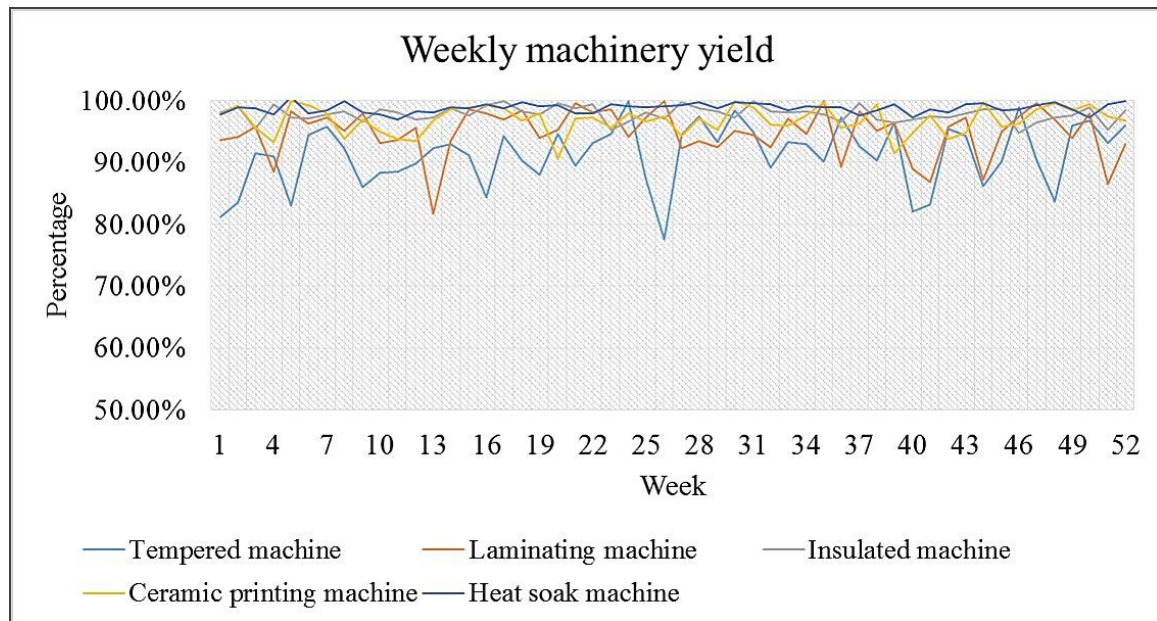


Figure 3. Weekly machinery yield

CU was calculated using expression 1. To get optimum output value, a simulation is run without machinery downtime and product reject (ideal condition), and it is found that the optimum output is 4848 units per week. CG is calculated using expression 2. The weekly CU and CG are shown in **Figure 4**. The total production output in the one-year simulation is 171,460 units or average weekly production output from the simulation is 3297 units. Consequently, the average CU is 68.01% and the CG is 31.99%. This finding aligns with previous research in other industries which found most industries run in 65% to 70% of capacity utilization [3,4]

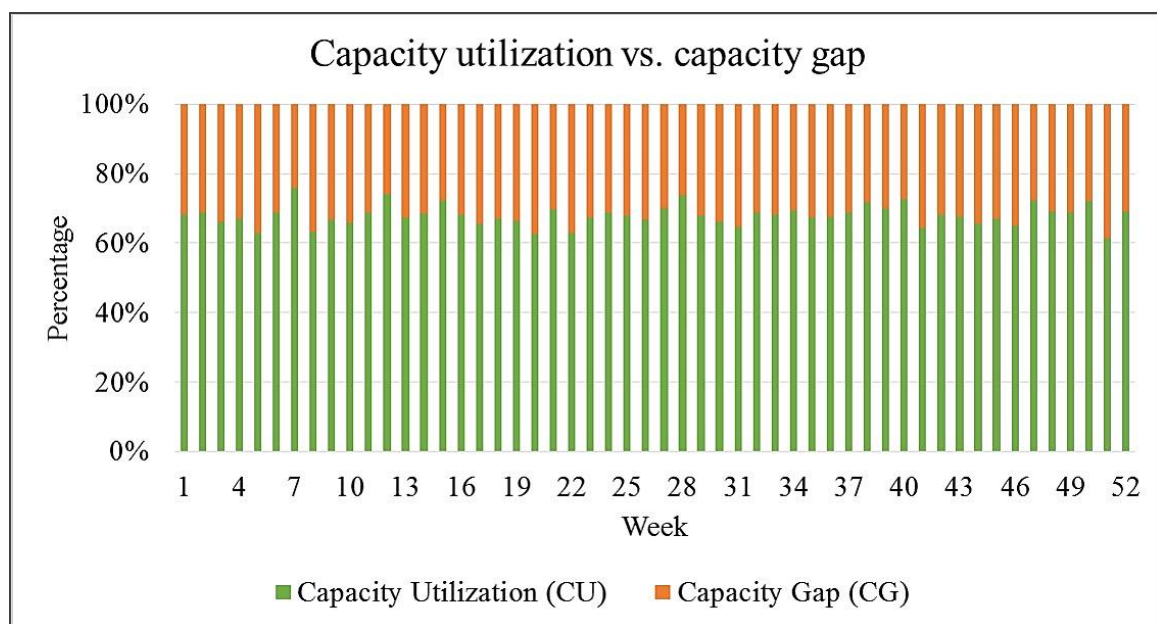


Figure 4. Capacity utilization vs. capacity gap

There is around 22% room for CU by improving machinery breakdown and product defective rate. Improving machinery breakdown and product defective rate will minimize the CG and at the same time will increase the output. Simulation is a good tool to study “what if” scenarios. In this study, two additional scenarios were run to predict the future capacity of the manufacturing system. The scenarios are as following:

1. Scenario 1 - Simulation of manufacturing system with stochastic machine breakdown variable.
2. Scenario 2 - Simulation of manufacturing system with stochastic product defective variable.

The comparison of total production output of simulation for 1 year is shown in **Table 2**, while **Figure 5** shown a comparison of weekly output.

Table 2. The comparison of simulation's total production output

Simulation	Current	Scenario 1	Scenario 2	Optimum
Output	171460	185445	236951	252096

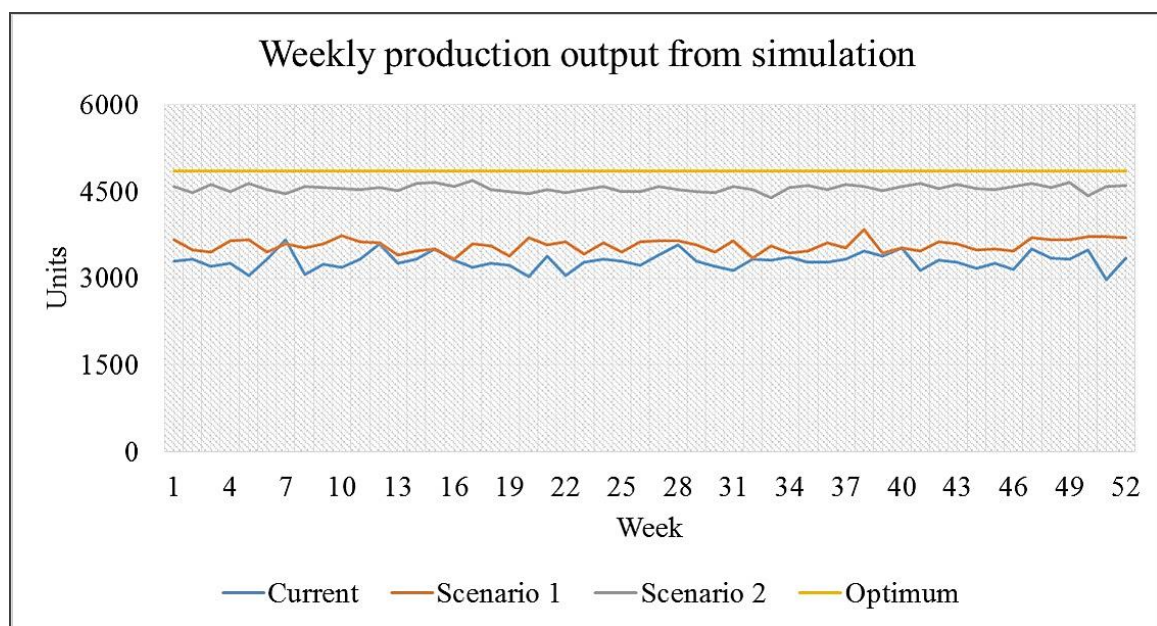


Figure 5. Weekly simulation's production output

It is found that if the manufacturing system can improve the production yield of 100% (zero defect), the output will increase by 8.16%, the capacity utilization improves to 73.56% and the capacity gap decrease to 26.44%. In the other scenario, if the manufacturing system improves the machinery up time by 100% (zero breakdowns) the output will increase by 38.20%, the capacity utilization improves to 93.99% and the capacity gap decrease to 6.01%.

6. Conclusion

This study addressed the capacity issue of a manufacturing system in its sustainability to meet future demand under stochastic variables such as machinery breakdown and product defective rate. The study revealed that machinery breakdown and product defective rate directly correlated with CU and CG in MTO type manufacturing system with high degree of product customizations. The study is important

because previous studies focused on the mathematical methodology to calculate CU using deterministic variables. Using simulation, operation level could play “what if” scenario to predict future capacity by improving machinery breakdown and product defective rate. However, this study lacks benchmarking of a similar type of manufacturing system. The information gathered from this study and model developed indeed may not represent the whole MTO manufacturing industry. Furthermore, this study only considered machinery breakdown and product defective rate as random variables in CU. Further study could include other random variables in the simulation to get more accurate results for decision-making. Stochastic characteristic of demand should also be considered to some extent to make the simulation closer to real-life situations.

7. References

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