

Simulation of mixed-load testing process in an electronic manufacturing company

Hayati Mukti Asih^{*1}, Chong Kuan Eng², Lee Mei Ph'ng³

¹Faculty of Industrial Technology, Ahmad Dahlan University,

Prof. Dr. Soepomo St., S.H., Warungboto, Yogyakarta, 55164, Indonesia

^{1,2}Faculty of Manufacturing Engineering, Universiti Teknikal Malaysia Melaka,
Hang Tuah Jaya 76100, Malaysia

³Centre for Languages and Human Development, Universiti Teknikal Malaysia Melaka,
Hang Tuah Jaya 76100, Malaysia

*Corresponding author, e-mail: hayati.asih@ie.uad.ac.id

Abstract

The automatic testing machine, called by mixed-load tester, has ability to load and test multiple product families in different testing durations simultaneously. However, the high product mixes for each product family undergoes a different process flow. In addition, the capability of the robot inside tester used for loading and unloading a product to each slot makes the capacity planning problem more complicated. It effects low tester utilization. This paper developed simulation models of capacity planning scenarios under demand and testing time uncertainty. These scenarios are built by robust optimization to handle worst case condition. The result shows the proposed solutions gives better tester utilization and improves the decision making process by providing more detailed and precise information about capacity planning under uncertainties that was not available in company's current method. To the best of our knowledge, this developed model is the first one considering the mixed-load tester under uncertainties.

Keywords: capacity planning, electronic industry, mixed-load tester, simulation, utilization

Copyright © 2019 Universitas Ahmad Dahlan. All rights reserved.

1. Introduction

The electronic industry has complex characteristics because of its high technology development, short product life cycle, and high products varieties and volumes. . Furthermore, many uncertainties which can influence the production performance occur in the real world. These uncertainties include machine breakdown [1], demand changes [2–7], processing time [8–10], cost parameter [4], capacity [11] and price [12–15]. So, electronic companies must have effective and efficient strategies to meet demand in right time, high quality and low cost. Hence, those strategies are challenging in order to provide high company profit.

Generally, simulation is an imitation of a system. Banks et al. [16] explained that the simulation model is developed based on the behavior system by considering a set of assumptions. Once the model is developed and validated, a model is able to study potential changes to predict its impact on the performance of the system.

Some operation systems are dynamic, integrated and complicated, especially in electronic industries. They require high investment of money each time that a new machine/tester, vehicle, or assembly line is launched. In addition, there are many uncertainties happened in the production system. Hence, it is hard to estimate the performance of productivity. Therefore, the computer simulation model is employed as a powerful tool to design, evaluate and redefine process within to overcome these problems.

Many researchers have developed simulation models in various application areas. Choi et al. [17] proposed a simulation model using ProModel to identify bottlenecks and evaluate the inventory and utilization in automotive foundry plant manufacturing. Melouk et al. [18] developed simulation optimization as a decision support tool to reduce work-in-process levels and utilization costs in steel manufacturing. Shao and Griffith [19] investigated hybrid simulation in Network for Earthquake Engineering Simulation (NEES) projects. Denkena and Winter [20] developed simulation-based planning of production capacity through integrative road mapping to reduce planning time and production cost in the wind turbine industry.

This paper is based on a case study of the multinational electronic industry in Malaysia, especially on the automatic testing process. It focuses on the development of a simulation model of capacity planning scenarios of mixed-load testers under demand and testing time uncertainty in complex real electronic industrial environment. Mixed-load tester is the capability of testers that can load and test multiple product families in different testing durations simultaneously. Currently, the company's capacity planner has frequent readjustment of the original plan generated because of these uncertainties. One of the main problems is low tester utilization. Therefore, the objective of this paper is to simulate the capacity planning scenarios of mixed-load tester under demand and testing time uncertainty and then evaluate its productivity improvement such as throughput and tester utilization.

The rest of the paper is organized as follows. Section 2 introduces the problem description. Section 3 describes the simulation model procedures for base model (current system) in a case company. Section 4 proposes experimentations of capacity planning scenarios under demand and testing time uncertainty. Section 5 presents the results and discussion. Finally, section 6 concludes the paper and recommends future research.

2. Research Method

This paper is based on a case study on automatic testing process at a multinational electronic industry in Malaysia. The problem is complex as the testers are employed to simultaneously load and test multiple product families, known as mixed-load tester. Each product family has several models with different testing durations. Apart from that, the high product mixes for each product family undergoes a different process flow. Currently, the customer demand and testing time are hardly to predict. It affects a company's capacity planner frequent adjustment to the original plan generated. In addition, the capability of the robot inside tester that is used for loading and unloading a product to each slot makes the capacity planning problem more complicated. It effects low tester utilization on the shop floor, increases the production cost and decreases the profit as well.

Figure 1 presents the process flow diagram of the automatic testing process. There are four main product families which have different process routes, input quantities and also testing times. Tester A consists of seven lines and Tester B consists of three lines. Product T is a product family which is only tested in Tester A. On the other hand, the other products (i.e. product A, product B and product S) are tested firstly at Tester A, and then at Tester B.

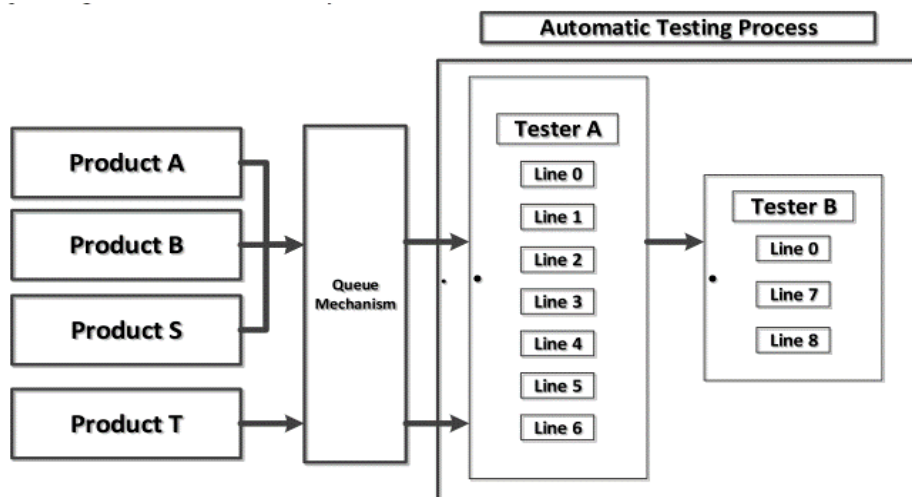


Figure 1. Process flow diagram of automatic testing process

The research method is presented in Figure 2. Firstly, the deterministic mathematical model of capacity planning was already developed in our previous research [21, 22]. Because of

the uncertainties of demand and testing time, Robust Optimization (RO) was employed to handle this by generating five scenarios according to robust parameter Γ values, known as robust mixed-load tester model (RMTM). Finally, the simulation model was built using ProModel® 7.5 Simulation Software to simulate those scenarios and evaluate effectiveness of the process in terms of throughput and tester utilization.

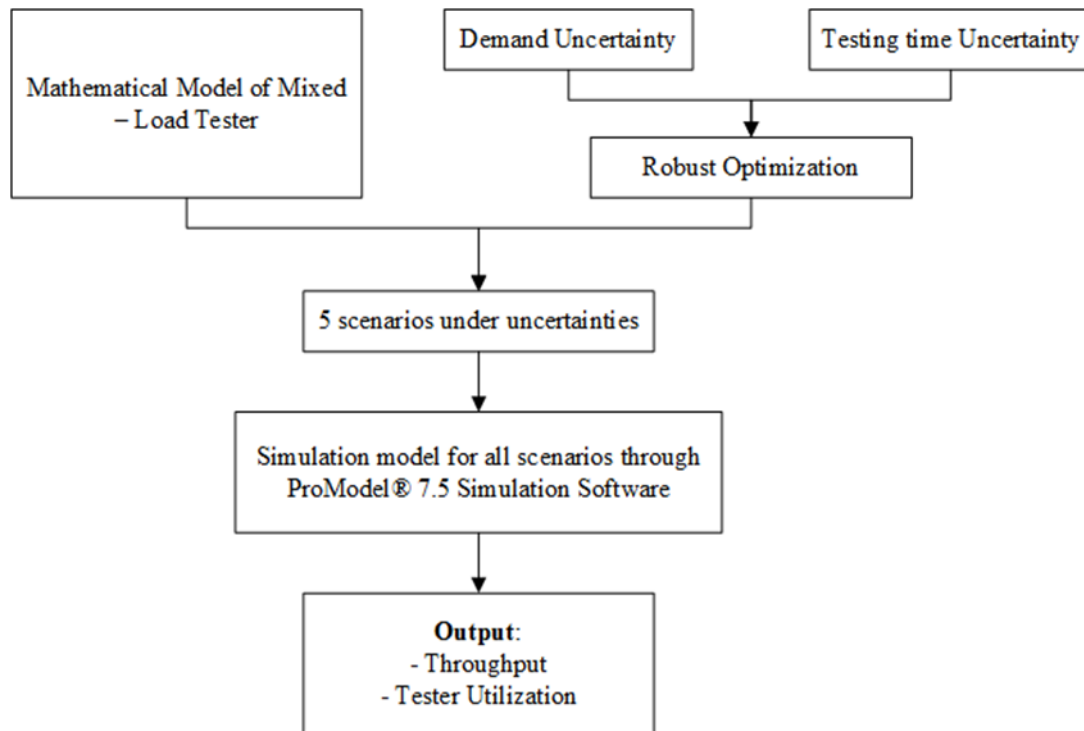


Figure 2. Research method

3. The Proposed Model

3.1. Simulation Model

The model of automatic testing process was built using ProModel® 7.5 simulation software. According to Harrel and Price [23], ProModel is a powerful and easy-to-use simulation tool to model all kinds of manufacturing system ranging from small job shop and machining cells to large mass production and flexible manufacturing system.

To build the base model of the automatic testing process, there are three main phases. The first phase developed a detailed process layout from which entities, location, resources, path network for resources and processes. After that, the logic for entity flows through locations including the testing time and graphics was built. In this base model, the automatic testing process consists of 45 units for Tester A and 11 units for Tester B.

The path is the track each resource uses to move or to process the entities. Every resource has different paths and different distances or time to travel. In the ProModel® 7.5 simulation software, these paths could be defined as the speed and distance or time, depending on the data collected.

For example, the paths of the operator and robots are presented in Figure 3. First of all, the products arrive at the buffer before the automatic testing process. Then, the feeder distributes those products to the small buffers input in each line. Once the product arrives to the small buffer input, the operator puts the product to the input conveyor in both testers. Then, the robot loads this product to slots in each tester and unloads the tested product to the output conveyor. Next, the operator takes the tested product into a small buffer output according to its product family. Finally, the feeder takes the tested product to the next station as shown in Figure 4. Those paths are connected and the resources automatically navigate the entities on the shortest path among those locations.

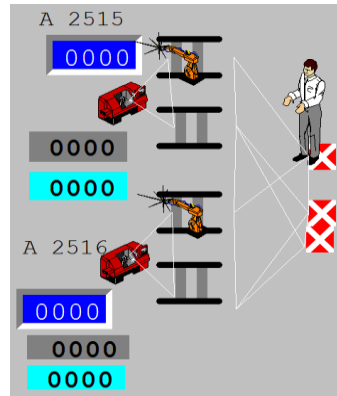


Figure 3. The operator and robot paths for the automatic testing process

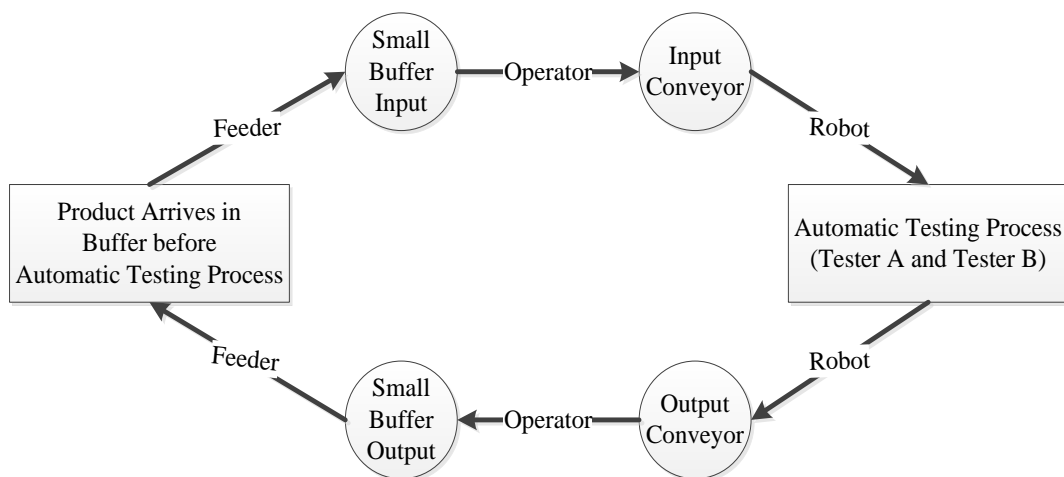


Figure 4. Activity cycle diagram of automatic testing process

There are some assumptions for this research, such as:

- 1) The rework, repair and return product are excluded.
- 2) The breakdown of the automatic tester and label printing machine is infrequent
- 3) The absenteeism of the operator and feeder are infrequent.
- 4) The plant runs continuously for 7-working days a week. Therefore, no shifts are modelled.
- 5) This automatic tester does not need any setup time.
- 6) The setup time of label printing is excluded.
- 7) Queue mechanism is FIFO (First-In-First-Out).

The second phase determined the warm-up and run length. Warm-up is used to avoid the misleading and the initialization bias. In this non-terminating simulation, Welch's method is employed to determine the period of warm-up. Welch's method is based on the computation of moving average based on those replications.

The graph of Welch's method shows a flat line at around 8 to 10 days. By considering the margin of safety when alternative scenarios are run, the warm-up is determined at the period of 8th day. Therefore, this warm-up period will be used for the experimentation. Then, run length in this paper was determined as 35 days. This is shown in Figure 5.

The third phase is verification and validation. First of all, it was conducted by having visual checking. It was conducted to ensure the right data and right logical model have been entered into the simulation model. The supervisor and the capacity planner of the electronic company verified the developed model, because they are the ones who have a detailed knowledge of the system being modelled. At the end of these three main phases, the base model using the ProModel® 7.5 Simulation Software is presented in Figure 6.

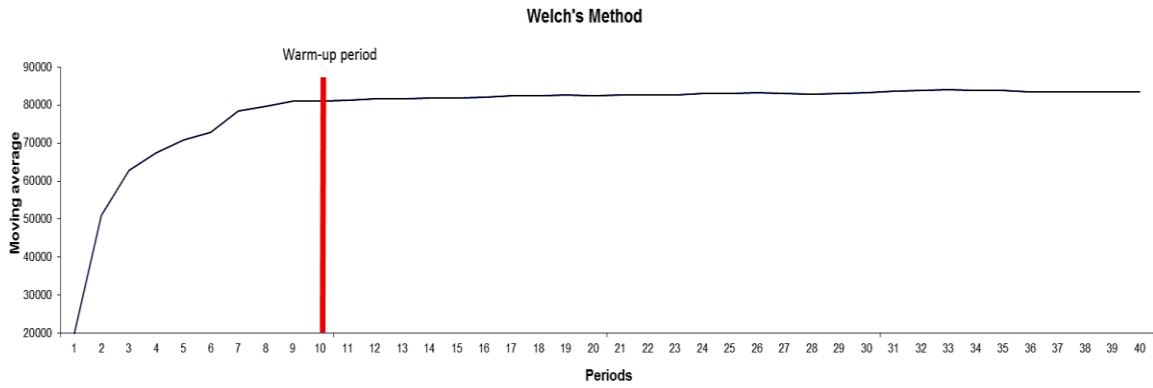


Figure 5. The warm-up determination

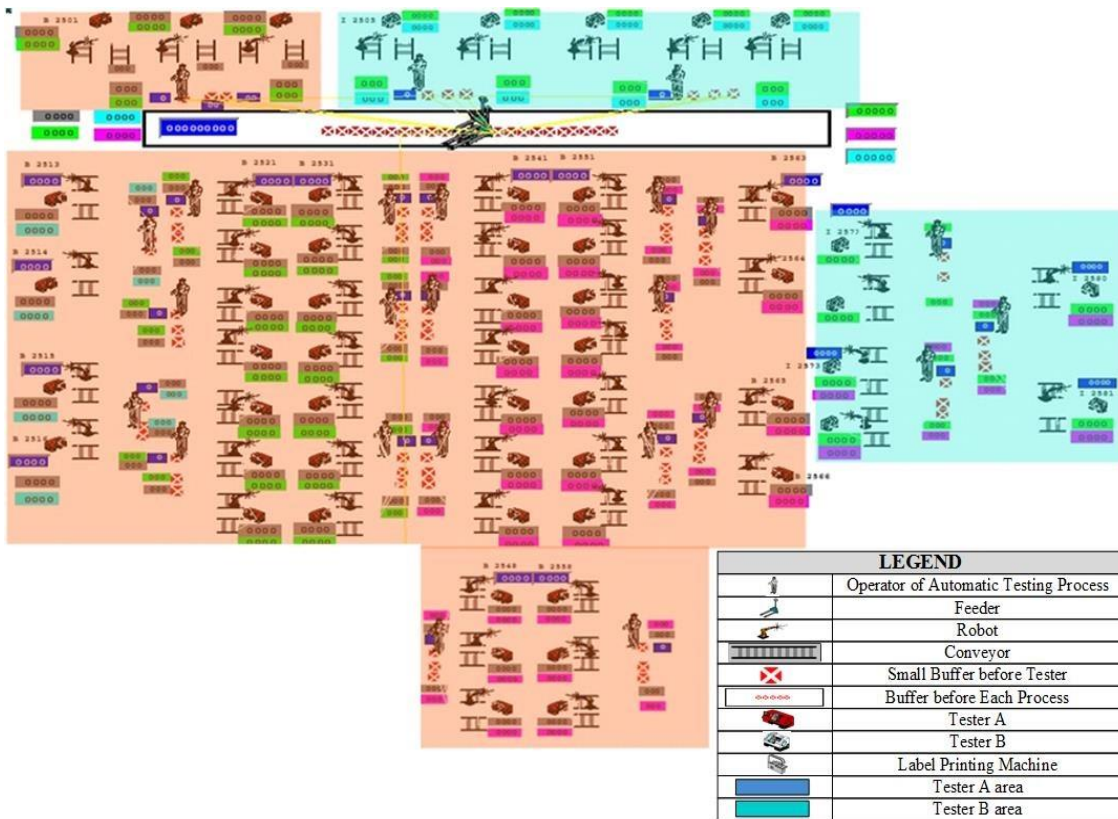


Figure 6. The base model in ProModel® 7.5 simulation software

3.2. Experimentation

This section describes how the simulation model evaluates the capacity planning scenarios of mixed-load tester under uncertainty. Uncertainty of customer demand and testing time for each product were the main concerns in the capacity planning because nowadays the company's capacity planner has frequent readjustment of the original plan generated because of these uncertainties. To deal with uncertainty, robust optimization (RO) is employed by controlling the degree of conservatism of generated plans through Γ parameter, known as budget of uncertainty [24].

The variability relative to customer demand and testing time for each product was considered to assess the robust model. In this sense, historical data were used to do capacity planning and allocation for the automatic testing process. There are three possible demand and

testing time value for each product, that is, nominal, low, and high. The nominal values is the average of the historical data. Then, the low and high value is the lowest and highest demand and testing time for both testers, respectively. The data of demand and testing time are presented in Table 1 and Table 2, respectively.

Table 1. Demand Data

	Low	Nominal	High
Product A	460	3131	13660
Product B	0	1210	4262
Product S	4126	9822	16798
Product T	45580	63187	83647

Table 2. Testing time Data for Tester A and Tester B

(i) Tester A				(ii) Tester B			
Product	Tester A (hours/unit)			Product	Tester B (hours/unit)		
	Low	Nominal	High		Low	Nominal	High
A	30.08	45.305	75.1	A	34.6	45.59	54.6
B	104.13	131.42	158.71	B	19.19	20.9	22.61
S	28.5	35.92	44.87	S	26.75	33.1075	39.19
T	13.63	17.36	18.56	T	-	-	-

The robust optimization model provided different scenarios for distinct Γ values, as showed in Table 3. In the nominal situation, when $\Gamma=0$, the robust model is equivalent to the deterministic model. It could be stated that there is no uncertainty in the model. The higher the robust parameter Γ values, the higher uncertainty occurs in the automatic testing process. In the fully protected situation ($\Gamma=4$), it will be penalized for all products (Product A, B, S, and T) with the highest value of customer demand and testing time for both testers. For instance, in scenario 2 for Tester A, $\Gamma=1$ means only one product is uncertain (assume it is Product T). Because of Product T is not tested in Tester B as shown in Figure 1, so the robust parameter $\Gamma=0$.

Table 3. Scenario of Different Robust Parameter Γ

Scenario	Robust parameter Γ	
	Tester A	Tester B
1	$\Gamma = 0$	$\Gamma = 0$
2	$\Gamma = 1$	$\Gamma = 0$
3	$\Gamma = 2$	$\Gamma = 1$
4	$\Gamma = 3$	$\Gamma = 2$
5	$\Gamma = 4$	$\Gamma = 3$

Furthermore, Table 4 is the result of the RO model by changing robust parameter Γ for each scenario. It shows the trade-off between the robustness and total expected number of testers in the automatic testing process. When $\Gamma=0$, the number of testers is the lowest one. On the other hand, with protection increase (increasing Γ), the probability of market loss reduces, while the number of testers increases. For the maximum protection case ($\Gamma=4$), it is the worst case scenario with the number of testers of 62 units and 24 units for Tester A and Tester B, respectively. Finally, these results are the input to build the simulation model for each scenario in order to throughput and tester utilization could be evaluated.

Table 4. Number of Testers Required for Each Scenario

Tester	Capacity Allocation	Scenario				
		1	2	3	4	5
A	T+S	15	18	29	23	19
	T+A	6	8	6	5	26
	T+B	7	8	6	21	17
	Total	28	34	41	49	62
B	S+A	6	6	10	8	21
	S+B	2	2	3	6	3
	Total	8	8	13	14	24

4. Results and Discussion

After base model was verified and validated, five scenarios were simulated using the ProModel® 7.5 simulation software. In this simulation mode, each scenario was developed based on the number of testers, demand and testing time from each Γ parameter. Finally, the productivity performances such as throughput and tester utilization were evaluated for each scenario.

Figure 7 presents the comparison results between the simulation and robust mixed-load tester model (RMTM) for different scenarios. The charts show that there is no big differences between simulation and RMTM for base model and all scenarios. It means this simulation model, as a tool that imitate real system, shows RMTM is validated and can be used as decision making that considers the uncertainties. In addition, all proposed scenarios achieved the production target.

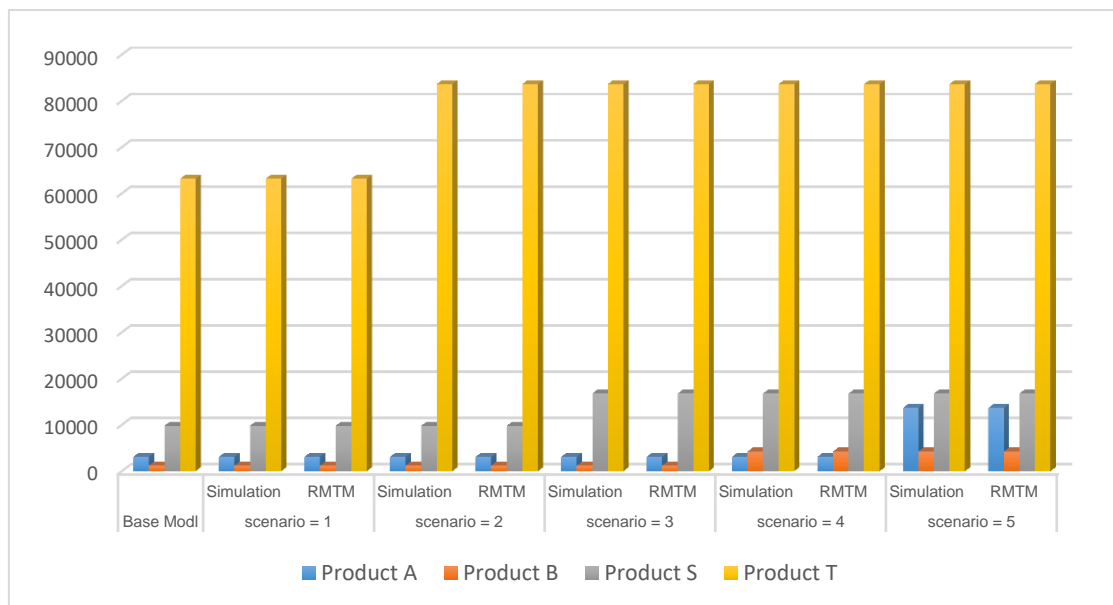


Figure 7. Throughput result: simulation vs robust mixed-load tester model (RMTM)

Another interesting output is tester utilization presented in Figure 8. It shows that the proposed solutions give higher utilization of both Tester A and Tester B than the base model. By having high utilization, the company could reduce the idle time in each tester and increase the tester efficiency.

The throughput of base model and scenario 1 which are almost similar. However, the number of tester in scenario 1 is lower than the base model. Furthermore, the tester utilization is higher than base model. As seen in Figure 8, the tester utilization of the base model is 67.68% for Tester P and 74.60% for Tester Q. All the proposed scenarios have achieved the utilization target, which is above 96%. It means that all proposed scenarios are able to become alternatives for the company during decision making for capacity planning of the mixed-load tester in the automated testing process as currently the company's capacity planner does not keep track of the variability of uncertain parameters such as customer demand and testing time in automatic testing process. It results in low accuracy of its planning and therefore needs re-adjustment of original capacity planning generated and effect to low tester utilization.

The significance of this research is the model's flexibility to represent the decision maker's perspective towards uncertainty. This robust mixed-load tester model permits adjustment of company's production manager's and capacity planner's attitude towards uncertainty through the Γ parameter.

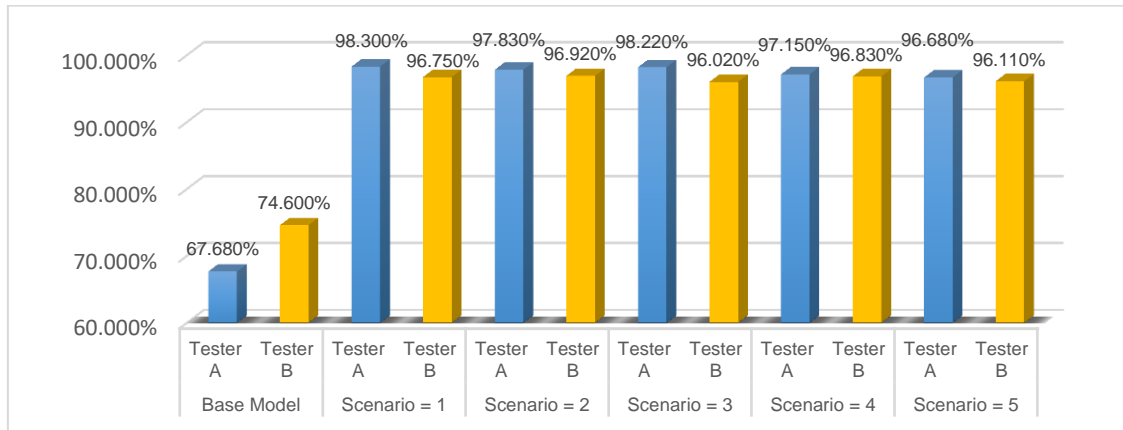


Figure 8. Tester utilization result

5. Conclusion and Future Research

This paper is based on a case study in an automatic testing time process of a multinational electronic industry in Malaysia. The problem was complex as the mixed-load tester has ability to load and test multiple product families simultaneously. Each product has different testing durations. The high product mixes for each product family undergoes a different process flow.

Nowadays, the customer demand and testing time are hard to predict. It affects to a company's capacity planner frequent adjustment to the original plan generated. In addition, the capability of the robot inside tester that is used for loading and unloading a product to each slot makes the capacity planning problem more complicated.

One of the main issues is low tester utilization. To handle this problem, the robust mixed-load tester model (RMTM) was developed by considering the uncertainties of demand and testing time. The objective of this paper is to simulate the scenarios generated from RMTM, then the performance measures are evaluated such as throughput and tester utilization.

The result shows all the proposed scenarios have higher tester utilization than current system while achieving the production target. For managerial insight, this proposed model helps manager and capacity planner to adjust uncertainties of demand and testing time through Γ parameter. It is able to improve the decision making process by providing more detailed and precise information about capacity planning and allocation problem under uncertainty that was not available in company's current method.

To the best of our knowledge, this computer simulation model is the first one considering the mixed-load tester under uncertainties. Most of the papers were about single load machine which the machines can only load a product family. For future research, another methods considering uncertainties could be employed.

Acknowledgement

This work was supported by UTeM Postgraduate Fellowship (Zamalah) Scheme from Universiti Teknikal Malaysia Melaka (UTeM), Malaysia, Malaysian International Scholarship (MIS) from Ministry of Higher Education, Malaysia, and Ahmad Dahlan University, Indonesia.

References

- [1] Xu J, Zeng Z. A discrete time optimal control model with uncertainty for dynamic machine allocation problem and its application to manufacturing and construction industries. *Applied Mathematical Modelling*. 2012; 36(8): 3513–3544.
- [2] Albey E, Norouzi A, Kempf KG, Uzsoy R. Demand Modeling with Forecast Evolution: An Application to Production Planning. *IEEE Transaction Semiconductor Manufacturing*. 2015; 28(3): 374–384.
- [3] Lin JT, Chen T, Chu H. A stochastic dynamic programming approach for multi-site capacity planning in TFT-LCD manufacturing under demand uncertainty. *International Journal of Production Economics*. 2014; 148: 21–36.

- [4] Maggioni F, Potra FA, Bertocchi M. A scenario-based framework for supply planning under uncertainty: stochastic programming versus robust optimization approaches. *Computational Management Science*. 2017; 14(1): 5–44.
- [5] Chou YC, Yang TC, Chen TS. Expansion of Finite Lifetime Capacity under Random Demand Shocks. *International Journal of Advanced Manufacturing Technology*. 2016; 89(5–8): 1901–1913.
- [6] Barahona F, Bermon S, Gunluk O, Hood S. Robust capacity planning in semiconductor manufacturing. *Naval Research Logistics*. 2005; 52(5): 459–468.
- [7] Ardjmand E, Weckman GR, Young WA, Sanei Bajgiran O, Aminipour B. A robust optimisation model for production planning and pricing under demand uncertainty. *International Journal of Production Research*. 2016; 54(13): 3885–3905.
- [8] Sakhaii M, Tavakkoli-moghaddam R, Bagheri M, Vatani B. A robust optimization approach for an integrated dynamic cellular manufacturing system and production planning with unreliable machines. *Applied Mathematical Model*. 2016; 40: 169–191.
- [9] Guo ZX, Wong WK, Leung SYS. A hybrid intelligent model for order allocation planning in make-to-order manufacturing. *Applied Soft Computing*. 2013; 13(3): 1376–1390.
- [10] Gyulai D, Kádár B, Monosotori L. Robust Production Planning and Capacity Control for Flexible Assembly Lines. *International Federation Automatic Control*. 2015; 48(3): 2312–2317.
- [11] Corolli L, Lulli G, Ntamo L. The time slot allocation problem under uncertain capacity. *Transportation Research Part C*. 2014; 46: 16–29.
- [12] Rentizelas AA, Tolis AI, Tatsiopoulos IP. Investment planning in electricity production under CO2 price uncertainty. *International Journal of Production Economics*. 2012; 140(2): 622–629.
- [13] Akbari K, Nasiri MM, Jolai F, Ghaderi SF. Optimal investment and unit sizing of distributed energy systems under uncertainty: A robust optimization approach. *Energy and Buildings*. 2014; 85: 275–286.
- [14] Verma A, Shukla N, Tyagi S, Mishra N. Stochastic modelling and optimisation of multi-plant capacity planning problem. *International Journal of Intelligent Engineering Informatics*. 2014; 2(2-3): 139–165.
- [15] Zhang Y, Jiang Y. Robust Optimization on Sustainable Biodiesel Supply Chain Produced from Waste Cooking Oil under Price Uncertainty. *Waste Management*. 2016; 60: 329–339.
- [16] Banks J, Carson JS, Nelson BL, Nicol DM. *Discrete-Event System Simulation*. Fifth Edition. New Jersey: Pearson Education, Inc. 2010.
- [17] Choi SD, Kumar AR, Houshyar A. *Manufacturing 3: A Simulation Study of An Automotive Foundry Plant Manufacturing Engine Blocks*. Proceedings of the 2002 Winter Simulation Conference. 2002: 1035–1040.
- [18] Melouk SH, Freeman NK, Miller D, Dunning M. Simulation optimization-based decision support tool for steel manufacturing. *International Journal of Production Economics*. 2013; 141: 269–276.
- [19] Shao X, Griffith C. An overview of hybrid simulation implementations in NEES projects. *Engineering Structures*. 2013; 56: 1439–1451.
- [20] Denkena B, Winter F. *Simulation-based Planning of Production Capacity through Integrative Roadmapping in the Wind Turbine Industry*. Procedia CIRP. 2015; 33: 105–110.
- [21] Asih HM, Eng CK. Throughput and tester utilization improvement in the hard disk drive assembly line using hybrid simulation approach. *Advanced Science Letter*. 2014; 20(2): 455-9.
- [22] Chong KE, Asih HM. An Integrated Robust Optimization Model of Capacity Planning under Demand Uncertainty in Electronic Industry. *International Journal of Mechanical and Mechatronics Engineering*. 2015; 15(3): 88–96.
- [23] Harrell CR, Price RN. *Simulation modeling using PROMODEL technology*. Proceedings of the Winter Simulation Conference. 2002; 192–198.
- [24] Carvalho AN, Oliveira F, Scavarda LF. Tactical Capacity Planning in A Real-World ETO Industry Case: A Robust Optimization Approach. *International Journal of Production Economics*. 2015; 167: 187–203.