# CAPACITY PLANNING AND PRODUCT ALLOCATIONS UNDER TESTING TIME UNCERTAINTY IN ELECTRONIC INDUSTRY

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**ABSTRACT:** Low utilization in automatic testing process has been plaguing hard disk drive manufacturers. This paper intended to optimize the number of testers while achieving the production target under testing time uncertainty in order to improve tester utilization. To handle the uncertainty, robust optimization was employed in the mixed-load tester model. The automatic tester was called mixed-load tester because of its ability to load and unload multiple product families simultaneously. The result showed the proposed model permitted adjustment of company`s production manager`s and capacity planner`s attitude towards testing time uncertainty through the robust parameters.

**KEYWORDS:** *Utilization; Robust Optimization; Stochastic Time*

## 1.0 INTRODUCTION

Capacity planning and product allocation are challenging issues in the electronic industry. Short product life cycle, high volume, product varieties and long processing time require companies to formulate good strategy to survive in this global competition.

This study was based on a case of multinational company manufacturing hard disk drive in Malaysia. This study focused on backend process specifically in automatic testing process. These testers are capable of supporting testing processes based on the products' configuration. The automatic tester employed in this case study is of newer technology and provides better quality outputs than the manual ones. These automatic testers have the ability to simultaneously load multiple product families namely mixed – load tester.

In automatic testing process, there are four product families that already represent 98% of total throughput, i.e. Product A, Product B, Product S and Product T. The product flow of each product family is presented in Figure 1. Product A, B and S are tested in Tester A, and then in Tester B. On the other hand, Product T is only tested in Tester A.

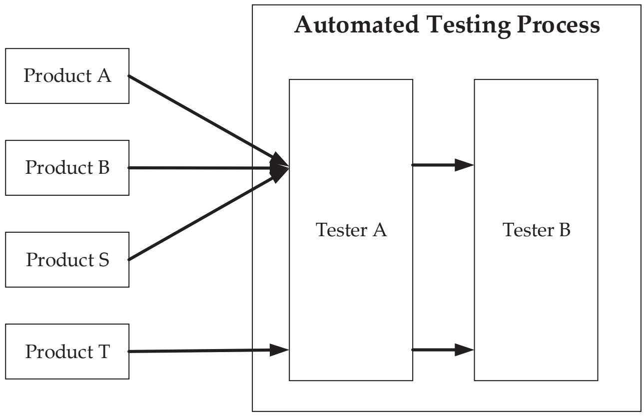


Figure 1: The product flow

The products in this company have wide varieties of product families and models. Each product family has several models with different testing durations. Each product family has its own process flows and production volumes. Another constraint is the existence of a robot inside each tester to load and unload a product to each cell. Therefore, the performance of the robot needs to be considered for allocating the products to tester. In addition, the uncertain testing time in real manufacturing system makes the problem more complicated. It affects re-adjustment planning that often occurs in shop floor and low tester utilization. Yusof and Deris [1] stated that one of the important performance measures in capacity planning is machine utilization. One of the ways to achieve it is by minimizing the number of machines required [2].

The complexity of automatic testing machine that has the ability to test multiple product families in parallel (which is called by mixed-load tester) makes the capacity planning and allocation more challenging. This aspect needs further research. In addition, uncertain testing time that often occurs in the shop floor makes the problem more complicated.

Therefore, this research proposed a novel hybrid methodology that integrates mathematical model and robust optimization to solve complex mixed-load tester model under testing time uncertainty.

## 2.0 LITERATURE REVIEW

Testing time is one of important parameters in planning the capacity and product allocation as this process has various product families and many models that each of them has long testing time. According to Hopp and Spearman [2], CP is about how much and what type of capacity to install and this decision creates a major impact on all other production planning issues (e.g., aggregate planning, demand management, sequencing and scheduling, shop floor control). Dolgui et al. [3] reviewed a state of the art of uncertain lead time in supply planning and inventory control. They explained that the fluctuation of lead time could influence the tool performance and high production cost, just as uncertain demand does. Martínez-Costa et al. [4] proposed a review on the mathematical modeling of strategic capacity planning in manufacturing company. In addition, Volling et al. [5] reviewed the planning of capacities and orders. They summarized the challenges of capacity planning in build-to-order automobile production as large networks that required an immense data volume and complex logistical interdependences. High uncertainty makes the planning difficult on evaluation and selection of mid and long-term plans, and also modeling of capacity because of high flexibility on most constraints, resulting in financial implication.

Dellaert et al. [6] developed capacity planning in hospital that considers waiting time. Haddadzade et al. [7] considered stochastic processing time in developing the integration of job shop scheduling and process planning through mathematical model and hybrid algorithm. Kacar et al. [8] developed a comparison of the performance of production planning model with and without non-integer lead time for wafer fabrication. Lin [9] proposed lead-time variability reduction problems for the integrated vendor– buyer supply chain system with partial backlogging under stochastic lead time. Rahdar et al. [10] investigated inventory control model under demand and lead time uncertainty by developing a tri-level optimization.

Another study focused on processing time uncertainty[11]. They proposed mixed-integer linear programming and robust optimization. The objective is to minimize the cost of machine breakdown and relocation, operator training and hiring, inter-intra cell part trip, and shortage and inventory. Gyulai et al. [12] developed simulation-based optimization method under uncertain processing time to have robust production planning and control in order to minimize the losses and production cost. In addition, Hu et al. [13] investigated single machine scheduling that considers uncertain processing time to maximize expected total weight of batches of jobs. Lv et al. [14] developed Monte Carlo algorithm for mixed-model assembly lines with uncertain processing time. The purpose was to minimize work overload at stations. Guirong and Qiqiang [15] investigated steelmaking-continuous casting production scheduling problem under processing time uncertainty by developing a cascade cross entropy algorithm. From the literature, only few papers consider processing time uncertainty in planning capacity and product allocation.

## 3.0 PROPOSED MODEL

This section elaborates the deterministic model and robust optimization model. The main objective of this proposed model is to improve tester utilization while achieving the production target under testing time uncertainty.

### 3.1 Deterministic Model

This model was formulated according to complex system characteristic of case company that considered mixed-load tester ( the tester has the ability to load and test multiple product families simultaneously).

In this model, the product families were divided into two groups; group X and Y. In Tester A, products in group X were for Product T; and products in group Y were for Product A, Product B, and Product S. On the other hand, in Tester B, Product S was included in group X; and products in group Y were for Product A and Product B. These combinations had been investigated in the previous study [16].

Using this strategy, one could balance the utilization of robot inside tester and the tester itself. Based on the observations conducted, one of the main issues was the robot had high utilization because of loading and unloading HDD to each slot. It made the slots in a tester are not totally full which resulted in low tester utilization. Hence, the combination and the number of products allocated to each tester were the most important issues in order to get better tester utilization and throughput.

The following notations are used to develop the models:

| | |
|---|---|
| m | index of tester stages; m = 1, … , M |
| x | index of product in group X; x = 1 |
| y | index of products in group Y; y = 1, … , Y |
| s | index of scenario; s = 1, … , S |

Parameters:

| | |
|---|---|
| $T_m^{req}$ | Number of testers required to test products in group *x* and group *y* in tester stage *m* |
| $T_m^a$ | Number of available testers required to test products in group *x* and group *y* in tester stage *m* |
| $T_{mx}$ | Number of testers in tester stage m for product group *x* |
| $T_{my}$ | Number of testers in tester stage m for product group *y* |
| $Q_{mx}$ | Turn of product in group *x* for tester stage *m* |
| $Q_{my}$ | Turn of product in group *y* for tester stage m |
| $t_{mx}$ | Testing time of product in group *x* for tester stage m |
| $t_{my}$ | Testing time of product in group *y* for tester stage *m* |
| $t_r$ | Travel time of robot |
| $D_x$ | Monthly demand of product in group *x* |
| $D_y$ | Monthly demand of product in group *y* |
| $N_{mx}$ | Hourly loading of product in group *x* for tester stage *m* |
| $N_{my}$ | Hourly loading of product in group *y* for tester stage *m* |
| $S_{mx}$ | Available slot of tester in tester stage *m* for product in group *x* |
| $S_{my}$ | Available slot of tester in tester stage *m* for product in group *y* |
| $S_m$ | Total slot (capacity) of tester in tester stage *m* |

$C_{mx}$ Allocated capacity of tester in tester stage m for product in group *x*

$C_{my}$ Allocated capacity of tester in tester stage *m* for product in group *y*

K Length of period in a day = 24 hours

The objective of this study was to minimize the number of testers required for both groups. It can be formulated as follows:

$$\text{minimize } Z = T_x - T_y \tag{1}$$

While Equation (2) presents the number of testers required which must not more than the available testers.

$$T_m^{req} \le T_m^{a} \tag{2}$$

The following equation is hourly loading of group X. It is to determine in an hour how many products that must be loaded in a tester. It is defined by dividing the demand of product in group X with all number of testers required then divided by the length of period in a day.

$$N_{mx} = \frac{D_x / T_m^{req}}{K} \tag{3}$$

Allocated capacity per tester for product in group X defines the number of products in group X allocated in a day. It can be mathematically expressed as follows:

$$C_{mx} = N_{mx} \times K \tag{4}$$

Equation (5) expresses the number of testers required for product in group X by dividing the demand product in group X and allocated capacity that is

$$T_{mx} = \frac{D_x}{C_{mx}} \tag{5}$$

Equation (6) shows the turn of product in group X which means how many the product in group X circulating in a day.

$$Q_{mx} = \frac{K}{t_{mx}} \times 95\% \tag{6}$$

The available slots for product in group X means how many slots needed per tester. It is by dividing the capacity and the turn of product in group X. It can be expressed as follows:

$$S_{mx} = \frac{C_{mx}}{Q_{mx}} \tag{7}$$

Meanwhile, Equation (8) presents the maximum slots in a tester for both tester stages.

$$1 \leq S_m \leq 2880 \tag{8}$$

Equation (9) offers a slot of the products in group Y. It can be defined by subtracting the total slots in a tester with slots for products in group X.

$$S_{my} = S_m - S_{mx} \tag{9}$$

Similar with group X, turn of product in group Y is the number of products in group Y allocated circulating in a day. It can be expressed as follows:

$$Q_{my} = \frac{K}{t_{my}} \times 95\% \tag{10}$$

Equation (11) expresses the number of allocated capacity for product in group Y in a tester. The constraint can be mathematically yielded as follows:

$$C_{my} = S_{my} \times Q_{my} \tag{11}$$

Hourly loading of product in group Y is the number of products that must be loaded in an hour. The formulation is given by

$$N_{my} = C_{my} \div K \tag{12}$$

Equation (13) is the total number of testers required for products in group Y such as

$$\sum_{y=1}^{Y} T_{my} = \sum_{y=1}^{Y} \frac{D_y}{C_{my}} \tag{13}$$

The standard travel time of a robot to load and unload product to each slot of a tester is 23.07 seconds. The constraint can be expressed as

$$t_r \leq 23.07 \tag{14}$$

The constraint below is robot capability inside each tester to load and unload product to each slot. The allocated capacity per tester of both group X and group Y must not exceed the travel time of a robot itself.

$$C_{mx} + C_{my} \leq \frac{K \times 3600}{t_r} \tag{15}$$

This constraint shows the number of required testers which must be equal to number of testers for the products in group Y and group X.

$$T_m^{req} = \sum_{y=1}^{Y} T_y = T_x \tag{16}$$

### 3.2 Robust Optimization (RO) Model

The RO was employed to handle uncertain testing time for mixed-load tester model. Considering the uncertainty, a parameter, Γ, is used to determine the number of product families whose demand and testing time will deviate from their nominal values. The parameter Γ is called the degree of conservatism, which reflects the decision makers` attitude toward risk. A larger Γ implies that decision makers has lower risk [2-3]. By considering the budget of uncertainty, Γ, the original constraint of testing time for all products in mixed-load tester model can be re-formulated as

$$t_{mx} = \sum_{s=1}^{S} Z_s \, t_{mxs} \tag{17}$$

$$t_{my} = \sum_{s=1}^{S} Z_s \, t_{mys} \tag{18}$$

$$\sum_{s=1}^{S} Z_s = 1 \tag{19}$$

$$\sum_{s=2}^{S} Z_s = \Gamma \tag{20}$$

$$Z_s \in \{0,1\} \tag{21}$$

By substituting Equation (17) into Equation (6) and Equation (18) into Equation (10), the robust counterpart of demand for both product groups are obtained where

$$Q_{mxs} = \frac{K}{\sum_{s=1}^{S} Z_s \, t_{mxs}} \times 95\% \tag{22}$$

$$Q_{mys} = \frac{K}{\sum_{s=1}^{S} Z_s \, t_{mys}} \times 95\% \tag{23}$$

## 4.0 RESULTS AND DISCUSSION

In calculating the proposed model, Microsoft Excel® and GeneHunter® optimization software were employed to optimize the number of testers. To handle testing time uncertainty, some scenarios were developed using historical data (Table 1). For instance, scenario 1 had nominal values for all products with robust parameter $\Gamma = 0$. Thus, there was no uncertainty in the shop floor. In scenario 2 with the robust parameter $\Gamma = 1$, only Product T that considered the uncertain testing time. On the other hand, scenario 5 was the worst – case plan as the uncertainty occured for all products.

The data were classified into three values, i.e. low, nominal, and high value. The nominal refers to the mean of testing time. Then, the low and high value refer to the lowest and the highest testing time of all models in each product family. It is presented in Table 2.

Table 1: Scenario of mixed-load tester model under testing time uncertainty

| Scenario | Product T | Product S | Product B | Product A |
|---|---|---|---|---|
| Scenario 1 Γ = 0 | Nominal value | Nominal value | Nominal value | Nominal value |
| Scenario 2 Γ = 1 | High value | Nominal value | Nominal value | Nominal value |
| Scenario 3 Γ = 2 | High value | High value | Nominal value | Nominal value |
| Scenario 4 Γ = 3 | High value | High value | High value | Nominal value |
| Scenario 5 Γ = 4 | High value | High value | High value | High value |

Table 2: Testing time values for each product family

| Testing time | Tester A | | | Tester B | | |
|---|---|---|---|---|---|---|
| | Nominal | Low | High | Nominal | Low | High |
| Product A | 45.305 | 30.08 | 75.1 | 45.59 | 34.6 | 54.6 |
| Product B | 131.42 | 104.13 | 158.71 | 20.9 | 19.19 | 22.61 |
| Product S | 35.92 | 28.5 | 44.87 | 33.1075 | 26.75 | 39.19 |
| Product T | 17.36 | 13.63 | 18.56 | - | - | - |

Table 3 shows the results of the proposed model for all scenarios. The results provided the minimum number of testers required of Tester A and Tester B. For instance, Γ = 0 which means no uncertainty occurred, the testers required for Tester A were 28 units and 8 units for Tester B. In Γ = 1, the number of testers required for Tester A were 28 units, and there was no calculation needed for Tester B as product T did not process there (see the product flow in Figure 1). After that, Γ = 4 which means the worst – case plan against uncertainty, number of testers required was the highest among another robust parameters Γ as testing time considered was high value for all product families.

Table 3: The result of capacity planning for all scenarios

| Scenario | Tester A | Tester B |
|---|---|---|
| Scenario 1 Γ = 0 | 28 | 8 |
| Scenario 2 Γ = 1 | 28 | - |
| Scenario 3 Γ = 2 | 30 | 9 |
| Scenario 4 Γ = 3 | 31 | 10 |
| Scenario 5 Γ = 4 | 32 | 10 |

The results of product allocation can be seen in Table 4 below. For example, this table explained Tester A in scenario 1, product S was allocated for 14 units; 6 units, 7 units, 28 units for product A, product B, and product T, respectively.

Table 4: The result of product allocation for all scenarios

| Scenarios | Tester A | | | | Tester B | | |
|---|---|---|---|---|---|---|---|
| | Product S | Product A | Product B | Product T | Product A | Product B | Product S |
| Scenario 1 | 14 | 6 | 7 | e28 | 6 | 2 | 8 |
| Scenario 2 | 15 | 6 | 7 | 28 | | | |
| Scenario 3 | 17 | 6 | 6 | 30 | 7 | 2 | 9 |
| Scenario 4 | 16 | 9 | 6 | 31 | 8 | 2 | 9 |
| Scenario 5 | 16 | 9 | 7 | 32 | 8 | 2 | 9 |

Interestingly, the proposed model that considered uncertain testing time had lower number of testers rather than the current system which has 45 units of Tester A and 11 units of Tester B. By minimizing the number of testers, the tester utilization could be improved and the production cost would be reduced, leading to higher company profit. The benefit of this result is decision makers of company can adjust which number of testers are required according to the level of risks. The higher the robust parameter Γ, the less risk that company faced.

## 5.0 CONCLUSION AND FUTURE RESEARCH

In this paper, the capacity planning and products allocation for mixed-load tester model under uncertain testing time are analyzed. The objective is to minimize the number of testers required while achieving the production target. To tackle the uncertainty, robust optimization is employed. Some scenarios are proposed according to historical data by considering the robust parameter Γ.

Numerical results based on real – world data indicate that number of testers required has linear relationship with the robust parameter Γ. The higher robust parameter, the less risk faced. Moreover, this result provides useful insights in helping the decision makers to cope with testing time uncertainty for planning capacity and allocating products of mixed – load tester model. This paper also provides model`s flexibility in representing the decision maker`s perspective towards uncertainty. This proposed model permits adjustment of production managers and capacity planners' attitude towards testing time uncertainty through the Γ parameter. For future research, some methods to handle uncertainties and some parameters of uncertainty might be employed for this model.

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