

Data Mining Analysis of Turn around Time Variation in a Semiconductor Manufacturing Line

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Abstract: Variation reduction of Turn Around Time (TAT) in a manufacturing line is one of the important issues for line optimization. In a manufacturing line with many sequential process steps such as semiconductor fabrication, it is not easy to find the root causes of the TAT variation because (1) there might be a big time gap (more than 30 days) between cause and effect, and (2) there are so many machines (or tools) related with a process. The purpose of this paper is to propose a data mining based method to identify the root cause of TAT variation. We also aim to validate the performance of the proposed method through a simulation study.

1 INTRODUCTION

We consider a Turn Around Time (TAT) reduction problem of a manufacturing line that consists of many sequential process steps such as semiconductor fabrication. Due to long time gap (more than 30 days) between cause and effect, it is difficult to make a timely solution. When engineers make a solution of the cause, the cause is not a current problem. Thus, in the field, a mostly used strategy for reducing TAT focuses on solving current problems of each machine under one's own supervision. However this strategy requires many human resources and does not provide priority of the causes because engineers do not know how much the cause will make an effect on the TAT. Furthermore, if there are many machines (or tools) in a manufacturing line, the problem becomes more difficult to assign the resource to solve the problem. Specially, when investing for buying new machines, identifying the true causes is very important because the cost of a machine is recently very expensive in a high technology industry.

The objective of this paper is to propose a data mining based method which identifies the root cause of TAT variation. Firstly, we build a relation model between time variables of each process step (e.g.,

tool processing, waiting time, etc.) and the TAT by using Partial Least Squares Regression (PLSR). Secondly, we calculate the VIP scores of importance of the time variables by applying the Variable Importance in the Projection (VIP) method to the PLSR model. We apply the proposed method to two simulation experiments which mimic the real situation. The result shows good performance. More exhaustive simulation study is underway.

The rest of the paper is organized as follows. A brief description of PLSR, the VIP method for selecting important variables, and the concept of the proposed method is given in Section 2. Section 3 describes the simulation design and experiment factors. Simulation results of two different cases are given in Section 4. Finally, Section 5 concludes the current work with a summary.

2 PROPOSED METHOD

2.1 VIP Method based on PLSR

2.1.1 Partial Least Squares Regression

In case of single response y and p variables, PLS regression model with h ($h \leq p$) latent variables can

be expressed as follows (Geladi, 1986; Eriksson, 2001).

$$X = TP^t + E \quad (1)$$

$$y = Tb + f \quad (2)$$

In Eq. (1,2), $X (n \times p)$, $T (n \times h)$, $P (p \times h)$, $y (n \times 1)$, and $b (h \times 1)$ are respectively used for variables, X scores, X loadings, a response, and regression coefficients of T . The k -th element of column vector b explains the relation between y and t_k , the k -th column vector of T . Meanwhile, $E (n \times p)$ and $f (n \times 1)$ stand for random errors of X and y , respectively. Generally, by using the Nonlinear Iterative Partial Least Squares (NIPALS) algorithm, a weight matrix $W (p \times h)$ is obtained to make $\|f\|$ (Euclidian norm) as small as possible and, at the same time, to derive a useful relation between X and y .

NIPALS algorithm: in case of single y

Assume that the $n \times p$ matrix X and the column vector y have been standardized to have mean 0 and unit variance. In the following, t_k , p_k , and w_k respectively stand for the k -th column vector of T , P , and W . The k -th latent variable is obtained iteratively as follows ($k = 1, 2, \dots, h$). Thus, model parameters in Eq. (1,2) are determined accordingly.

- Step 1 $y^{(k)} \leftarrow y^{(k-1)} - b_{k-1} t_{k-1}^t$; $y^{(1)} \leftarrow y$
and $X^{(k)} \leftarrow X^{(k-1)} - t_{k-1}^t p_{k-1}^t$; $X^{(1)} \leftarrow X$
- Step 2 $w_k^t = y^{(k) t} X^{(k)} / y^{(k) t} y^{(k)}$
- Step 3 $w_k \leftarrow w_k / \|w_k\|$
- Step 4 $t_k = X^{(k)} w_k / w_k^t w_k$
- Step 5 $p_k^t = t_k^t X^{(k)} / t_k^t t_k$
- Step 6 $t_k \leftarrow t_k / \|p_k\|$
- Step 7 $w_k \leftarrow w_k / \|p_k\|$
- Step 8 $p_k \leftarrow p_k / \|p_k\|$
- Step 9 $b_k = y^{(k) t} t_k / t_k^t t_k$

Here, a variable selection method using PLS regression will be considered.

2.1.2 VIP Method

The VIP score of a variable is a summary of the importance for the projections to find h latent variables (Wold, 1993). The VIP method shows excellent simulation results in identifying important variables when multicollinearity is present (Chong, 2005).

The VIP score for the j -th variable can be calculated by Eq. (3). On the other hand, since the average of squared VIP scores equals 1, 'greater than one rule' is generally used as a criterion for variable selection.

$$VIP_j = \sqrt{\frac{p \sum_{k=1}^h (SS(b_k t_k) (w_{jk} / \|w_k\|)^2)}{\sum_{k=1}^h SS(b_k t_k)}} \quad (3)$$

where $SS(b_k t_k) = b_k^2 t_k^t t_k$

2.2 Cause Analysis of TAT Variation

In this section, we describe the proposed method to find causes for TAT variation using the VIP method. We consider a manufacturing process line which consists of S sequential process steps. There are historical data having N production observations. Let t_{is} and w_{is} be tool and waiting time in s -th step for the i th production ($i=1, 2, \dots, N$). Now, we prepare historical data

$$\{(y_i, x_i), i = 1, 2, \dots, N\}$$

where $\{x_i = (t_{i1}, t_{i2}, \dots, t_{iS}, w_{i1}, w_{i2}, \dots, w_{iS})\}$ (4)

In (4), y_i and x_i are the TAT variable and S tool and waiting time variables for the i th production. The VIP scores for S tool and waiting time variables are obtained by firstly building the PLSR model from the dataset (4) and secondly applying the VIP method. We select tool and waiting time variables with VIP score greater than 1 as the major causes highly related to the TAT variable.

3 SIMULATIONS

3.1 Design of Simulation

We generate datasets in Eq. (4) by running a simulation manufacturing model defined as Eq. in (5). We assume that a simulation manufacturing model consists of 8 sequential process steps (i.e., $S_1 \rightarrow S_2 \rightarrow \dots \rightarrow S_8$) and TAT, y_i follows a linear model having S tool and waiting time variables as Eq. in (5).

$$y_i = \sum_{s=1}^8 (t_{is} + w_{is})$$

$$\text{where } t_{is} \stackrel{iid}{\sim} N(1, \sigma^2), (i=1, 2, \dots, N) \quad (5)$$

In Eq. (5), tool time variables follow the normal distribution and waiting time variables are determined by simulation runs as Eq. (6).

$$w_{is} = \text{process_start_time}_{is} - \text{process_end_time}_{i(s-1)} \quad (6)$$

3.1.1 Production Order

At each simulation time, production order occurs with probability p and the volume of each order is

the ceiling value of a uniform random variable from the uniform distribution $(0, b)$ as in Eq. (7, 8).

$$\text{event that an order occurs} \sim \text{Bernoulli}(p) \quad (7)$$

$$\text{order volume} \sim [\text{Unif}(0, b)] \quad (8)$$

So, the expected order volume at each simulation time is as in Eq.(9).

$$\begin{aligned} E(\text{daily order volume}) &= E(\text{order occurs}) \times E(\text{volume}) \\ &= p \times \frac{(b+1)}{2} \end{aligned} \quad (9)$$

3.1.2 Tool Time in Abnormal Status

There are two kinds of abnormal status in a tool: (i) mean shift and (ii) variation increase. In s -th process step, we generate the abnormal tool time from Eq. (10).

$$t_{is} \stackrel{iid}{\sim} N(1 + t_{\text{abnormal}}, k\sigma^2), \quad (i=t_{\text{abnormal start}}, \dots, t_{\text{abnormal end}}) \quad (10)$$

3.2 Experimental Factors

There are eight simulation experiment factors as in Table 1 to mimic a manufacturing line which consists of many sequential process steps.

4 RESULTS

In this paper, we consider a sequential line which consists of eight processes. We fixed the number of product mix and variation of tool time under normal status of Table 1 to 1 and $(1/12)^2$ respectively.

4.1 Case 1: Mean Shift of Tool Time

Table 1: This summarizes simulation experiment factors.

Factors	Levels or description
No. of process steps	8, 80, 800
Production order rate	Bernoulli(p)
Volume of order	Ceiling value of Unif($0, b$); b is an integer.
No. of product Mix	1, 2, 3
Variance of tool time under normal status	σ^2 in Eq. (5)
Variation ratio of tool time under abnormal status	k in Eq. (10)
Mean shift of tool time under abnormal status	t_{abnormal} in Eq. (10)
Time period of abnormal status	$[t_{\text{abnormal start}}, t_{\text{abnormal end}}]$ in Eq. (10)

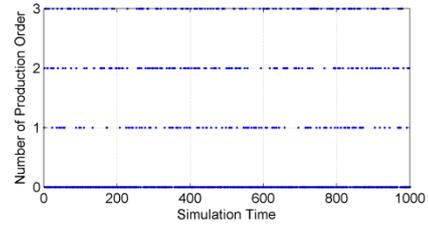


Figure 1: This shows an example of production order (experiment parameter $p = 0.4$ and $b = 3$).

We assumed that production order is the Bernoulli random variable with probability $p = 0.4$ and the volume of order is the ceiling value of random value generated from the Uniform distribution with parameters 0 and 3. Thus, the expected production order per simulation unit time is 0.8 by Eq. (9). Figure 1 shows an example of production order along the simulation time from 1 to 1,000.

We assumed two abnormal steps having mean shift of tool time as in Eq. (11) and Eq. (12).

$$t_{i(s3)} \stackrel{iid}{\sim} N(1 + 0.3, (1/12)^2), \quad i \in [300, 350] \quad (11)$$

$$t_{i(s6)} \stackrel{iid}{\sim} N(1 + 0.3, (1/12)^2) \quad (12)$$

$i \in [450, 460] \text{ or } [550, 560] \text{ or } [650, 660] \text{ or } [750, 760] \text{ or } [850, 860]$

Figure 2 shows the trend of tool time of all process steps. Tool time varies around 1 except Step 3 and Step 6.

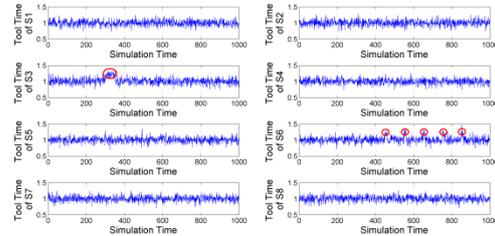


Figure 2: Mean shift of tool time is assumed in Step S3 and S6. Red circles denote mean shift of tool time.

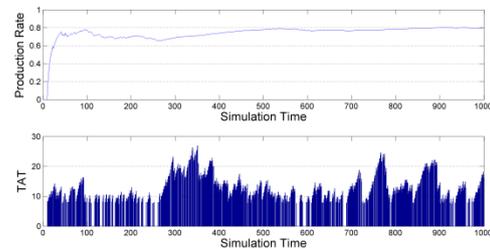


Figure 3: The range of TAT is about 20 unit time in the case 1 (experiment parameter $p = 0.4$ & $b = 3$).

Figure 3 shows simulation results of production rate (= number of all processes completed products per unit simulation time) and TAT over the simulation time. TAT ranges from 7.5 to 26.9.

Table 2: Variables with VIP scores greater than 1 are important ones which affect the variation of TAT.

Rank	Variable Name	VIP Score
1	Waiting Time in Step 1	2.44*
2	Waiting Time in Step 2	1.79*
3	Waiting Time in Step 3	1.55*
4	Waiting Time in Step 6	1.29*
5	Waiting Time in Step 5	0.83
6	Waiting Time in Step 7	0.74
7	Tool Time in Step 3	0.71
8	Waiting Time in Step 4	0.71
9	Waiting Time in Step 8	0.50
10	Tool Time in Step 5	0.30
11	Tool Time in Step 1	0.27
12	Tool Time in Step 4	0.21
13	Tool Time in Step 6	0.19
14	Tool Time in Step 7	0.09
15	Tool Time in Step 8	0.08
16	Tool Time in Step 2	0.08

To discover the cause of TAT variation, the proposed method was applied. Table 2 shows the results of the VIP scores. We selected four variables with VIP scores greater than 1 as important variable highly related with TAT variation (waiting time in S1, S2, S3, and S6). The method found all of two intended abnormal variables (waiting time in S3 and S6). Furthermore, the method indicated that random batch order most affects the TAT variation (waiting time in S1 and S2).

4.2 Case 2: Variation Increase of Tool Time

In this case, we assumed abnormal status in S3 and S6 step where the variance of tool time increases as in Eq. (13) and Eq. (14). Figure 4 shows the trend of tool time of S3 and S6 step over the simulation time.

$$t_{i(s3)} \stackrel{iid}{\sim} N(1, (1/4)^2), i \in [300,350] \quad (13)$$

$$t_{i(s6)} \stackrel{iid}{\sim} N(1, (1/4)^2) \quad (14)$$

$i \in [450,470] \text{ or } [550,570] \text{ or } [650,670] \text{ or } [750,770] \text{ or } [850,870]$

To create production order, we set experiment parameters as $p = 0.5$ and $b = 3$. The range of TAT is 37 unit simulation time as shown in Figure 5 (from 40.3 to 77.4 unit simulation time after 200 unit simulation time).

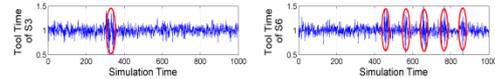


Figure 4: Variance increase of tool time is assumed in Step S3 and S6. Red circles denote variance increase of tool time.

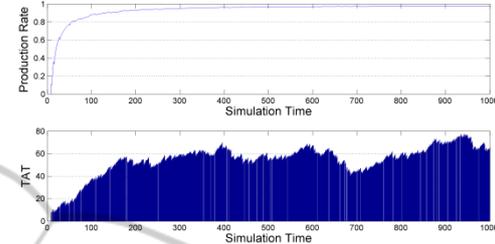


Figure 5: The range of TAT is about 37 unit time in the case2 (experiment parameter $p = 0.5$ & $b = 3$).

To identify causes of the variance, we applied the proposed method and obtained the VIP scores as in Table 3. The method selected four variables as important ones: waiting time in S1, S3, S7, and S6. All of two intended abnormal variables (S3 and S6) were found.

Table 3: Variables with VIP scores greater than 1 are important ones which affect the variation of TAT.

Rank	Variable Name	VIP Score
1	Waiting Time in Step 1	2.90*
2	Waiting Time in Step 3	1.62*
3	Waiting Time in Step 7	1.61*
4	Waiting Time in Step 6	1.01*
5	Waiting Time in Step 4	0.69
6	Waiting Time in Step 5	0.61
7	Waiting Time in Step 2	0.45
8	Waiting Time in Step 8	0.33
9	Tool Time in Step 2	0.30
10	Tool Time in Step 5	0.17
11	Tool Time in Step 4	0.15
12	Tool Time in Step 3	0.15
13	Tool Time in Step 7	0.10
14	Tool Time in Step 6	0.09
15	Tool Time in Step 8	0.07
16	Tool Time in Step 1	0.07

4.3 Latent Variable Analysis

We can visualize all observations of data used in Case 2 with only two latent variables obtained from PLSR model as shown in Figure 6. It seems like there are several clusters along the simulation time. There would be different important variable sets

according to the cluster. Research regarding this issue is underway.

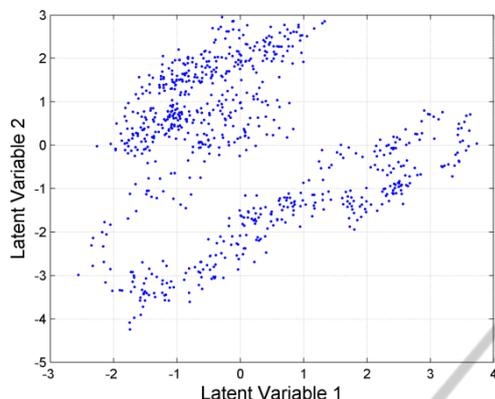


Figure 6: Several clusters are found by dotting with first and second latent variables of PLS regression. The same data in Case 2 were used.

5 CONCLUSIONS

In this paper, we propose a data mining based method to find the causes of the variation of TAT in a manufacturing line with many sequential process steps. In our simulation case studies, the method performed well. Exhaustive simulation study and research about the relationship between variables and TAT are currently underway.

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