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Learning curve analysis in total productive maintenance

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Abstract

The continuous improvement concepts such as total quality management, just-in-time and total productive maintenance have been widely recognized as a strategic weapon and successfully implemented in many organizations. In this paper, we focus on the application of total productive maintenance (TPM). A random effect non-linear regression model called the Time Constant Model was used to formulate a prediction model for the learning rate in terms of company size, sales, ISO 9000 certification and TPM award year. A two-stage analysis was employed to estimate the parameters. Using the approach of this study, one can determine the appropriate time for checking the performance of implementing total productive maintenance. By comparing the expected overall equipment effectiveness (OEE), one can improve the maintenance policy and monitor the progress of OEE.

Keywords: Learning curve; Overall equipment effectiveness; Total productive maintenance

1. Introduction

Many systems in practice today do not perform as intended, nor are they cost effective in terms of their operation and support. Manufacturing systems, in particular, often operate at less than full capacity. Consequently, productivity is low and the cost of producing products is high. In dealing with the aspect of cost, experience has indicated that a large percentage of the total cost of doing business is due to maintenance-related activities in the factory (i.e., the costs associated with maintenance, labor and materials and the cost due to production losses). Further, these costs are likely to increase even more in the future with the added complexities of factory equipment through the introduction of new technologies, automation, the use of robots, and so on. In response to maintenance and support problems in the typical factory environment the Japanese in 1971, introduced the concept of total productive maintenance (TPM), an integrated life cycle approach to factory maintenance and support. Since then, TPM methods and techniques have been successfully implemented in Japan, and later on in some other advanced and advancing countries in the world. Inherent within the TPM concept are the aspects of enhancing the overall effectiveness of factory equipment, and providing an optimal group organizational approach in the accomplishment of system maintenance activities. Both the equipment and the organizational sides of the spectrum need to be addressed in fulfilling the objectives of TPM. It is believed that while many successes have been realized in structuring organizations to respond better to the maintenance challenge, very little progress has been made in relation to the prediction of total equipment utilization while implementing TPM. In this paper, we focus on the application of TPM. A random effect non-linear regression model called the Time Constant Model [1] was used to formulate a prediction model for the learning rate in terms of company size, sales, ISO 9000 certification and TPM award year. A two-stage analysis was employed to estimate the parameters. Using the approach of this study, one can determine the appropriate time for checking the performance of implementing total productive maintenance. By comparing the expected overall equipment effectiveness (OEE) one can improve the maintenance

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policy and monitor the progress of OEE. The literature review on learning curves and TPM studies is presented in the following section. The learning curve analysis in TPM is discussed in Section 3, followed by some examples to demonstrate the application of the proposed methodology. The conclusions are made in the final section.

2. Literature review

Learning curves have been extensively studied, starting with Wright in 1936, and have been applied in practice [2]. It has been observed that every time the cumulative production volume doubles, the marginal cost diminishes by a fixed proportion (i.e., one minus the so-called learning rate). In that sense, the learning curve function is a power function with respect to the cumulative production volume. Learning rates are often similar to the same line of products [3]. However, Argote and Epple [4] report that organizations vary considerably in their learning rates for manufacturing the same products.

Muth [5] provides a survey of the theories that attempt to explain the learning curve phenomenon and propose a theory based on a random search within a fixed population of technological possibilities. Adler and Clark [6] propose a learning process model that relates the productivity improvement in an electric equipment company to first-order learning (cumulative output) and second-order learning (i.e., engineering changes and work force learning). Zangwill and Kantor [7] propose a model for continuous improvement activities and relate it to three forms of learning curves.

Few researchers have discussed the application of the learning curves in product quality and process improvement. Schneiderman [8] provides the times to halve the defect rates for many processes using a learning curve model that relates the logarithms of defect level to time. The paper reports the importance of identifying and setting targets for managing improvement activities. Comptom et al. [9] propose three learning models related to quality—the power form, the exponential form, and the linear form. In these, a measure of quality improvement (or quality index) is expressed as a function of cumulative volume.

For comprehensive surveys of the learning curve models, the reader is referred to Yelle [2], Hacket [10], Towill [11], and Badiru [12]. However, all papers mentioned in these studies address improvement measured by means of either productivity or product quality. In this paper, we address learning by means of overall equipment effectiveness (OEE).

Total productive maintenance, proposed by Seiichi Nakajima, has been widely applied for its benefits to the maintenance deliver system since 1971 [13]. The word “total” in total productive maintenance has three meanings that describe the principal features of TPM:

(1) Total effectiveness (including productivity, cost, quality delivery, safety, environment and health, morale).
(2) Total maintenance system (including maintenance prevention (MP), maintainability improvement (MI)).
(3) Total participation of all employees.

Thus, the goal of TPM is to increase the productivity of plant and equipment through company-led small group activities and autonomous maintenance by operators. To maximize output, the most efficient way is to eliminate causes, the so-called *six big losses* in TPM that reduce equipment effectiveness. (Six losses are: (1) reduced yield—from start up to stable production, (2) process defects, (3) reduced speed, (4) idling and minor stoppages, (5) set-up and adjustment, and (6) equipment failure.)

In the evaluation of a maintenance performance, OEE is used as a metric to evaluate the manufacturing capability. OEE is a function of equipment availability, performance efficiency, and quality. That is,

$$\text{OEE} = (\text{availability}) \times (\text{performance efficiency}) \quad (\text{quality rate}),$$

where

$$\text{availability} = \frac{\text{loading time} - \text{downtime}}{\text{loading time}}$$

$$\begin{aligned}\text{performance efficiency} &= \text{operating speed rate} \times \text{net operating rate} \\ &= \frac{\text{theoretical cycle time}}{\text{actual cycle time}} \times \frac{\text{process amount} \times \text{actual cycle time}}{\text{operating time}} \\ &= \frac{\text{theoretical cycle time} \times \text{process amount}}{\text{operating time}}\end{aligned}$$

$$\text{quality rate} = \frac{\text{processed amount} - \text{defect amount}}{\text{processed amount}}.$$

An 85% OEE is considered as being world class and a benchmark to be established for a typical manufacturing capability. In practice, achieving an 85% OEE and obtaining a prize-winning award are objectives of firms when implementing TPM. Typically, it takes an average of three and a half years from introduction of TPM to achieve prize-winning results.

Several books and articles have presented TPM improvement activities in plants and, based on case studies, suggested the implementation procedures [14–19]. However, both Enkawa [20] and Miyake and Enkawa [21] develop in-depth systematized comparisons under the perspective of analyzing mutual complementary between total quality control (TQC) and TPM.

McKone et al. [22] propose a theoretical framework by testing how the contextual issues affect firms’ maintenance systems when implementing TPM. Their studies show that the proposed three contexts—environmental context (country, industry), organizational context (equipment age, equipment type, company size, plant age, unionization), and managerial context (just-in-time, total quality management, employee involvement)—do influence the firms' TPM adoptions at different levels. Our study followed the step of McKone et al., however, by empirically studying how some of contextual issues affect firms' maintenance performance in terms of OEE. That is, the effects of some contextual issues, such as total quality management, country, and company size, will be tested against the firms' maintenance performance in terms of OEE.

3. The learning curve analysis in TPM

A random effect learning curve analysis is used to develop a prediction model for monitoring the improvement of implementing TPM, such as the value of OEE. The analysis of a random effect learning model has been extensively used in biomedical research [23–25]. In general, the goal of the learning curve analysis is to estimate learning rates of a principal attribute in terms of concurrent characteristics that do not change over the experimental period. Using a two-stage model typically carries out the growth curve analysis. The first stage consists of the within-individual non-linear regression model in which the learning rates for the serial observations are estimated for all individuals. The second stage consists of a between-individual model in which the estimates of the learning rates are related to a set of covariates. The Time Constant learning curve model has been found to be a good descriptor of many industrial performance improvement situations [1]. Here, the within-individual model for the learning curve in TPM is given as follows:

$$Y(t) = Y_c + Y_f(1 - \mathrm{e}^{-(t/\tau)+\varepsilon}), \tag{1}$$

where $Y(t)$ is the OEE (%) at time t, Y_c the initial level of OEE (%), Y_f/Y_c the dynamic gain of OEE (%), τ the time constant (months) (a measure of how long it takes to achieve growth in performance) and ε the homoscedastical, serially non-correlated error term $\sim N(0, \sigma^2)$.

The initial level of OEE (%), Y_c, the parameter of Y_f, and the time constant, τ, may be varied depending mostly on associated company culture and the types of manufacturing products. In addition, some variations of the learning index cannot be explained by these characteristics. The model, in which the rate of improvement, τ, was considered as a function of the random error, is called the between-individual model and given as follows:

$$\tau = \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \cdots + \gamma_m x_m + \delta, \tag{2}$$

where x_i can be the size of company, sales, certified as ISO 9000 or not, and the number of years from starting the TPM program to winning the TPM award, etc.

In order to estimate the parameters in Eqs. (1) and (2), a two-stage procedure is used in this study. At the first stage the learning index in the within-individual model is estimated using a non-linear regression method. A method widely used in computer algorithms for non-linear regression is linearization of the non-linear function followed by the Gauss-Newton iteration method of parameter estimation [26]. Linearization is accomplished by a Taylor series expansion of $f(t_i, \theta)$ about the point $\theta_0^{\mathrm{T}} = [\theta_{10}, \theta_{20}] = [Y_{c0}, Y_{f0}, \tau_0]$ with only the linear terms retained. This yields

$$f(t_i, \theta) = f(t_i, \theta_0) + \sum_{j=1}^{3} \left[\frac{\partial f(t_i, \theta)}{\partial \theta_j} \right]_{\theta=\theta_0} (\theta_j - \theta_{j0}). \tag{3}$$

We may rewrite the above equation as follows:

$$y_0 = Z_0 x_0 + \varepsilon, \tag{4}$$

where

$$y_0 = f(t_i, \theta) - f(t_i, \theta_0),$$

$$Z_0 = \left[\left[\frac{\partial f(t_i, \theta)}{\partial \theta_1} \right]_{\theta=\theta_0}, \left[\frac{\partial f(t_i, \theta)}{\partial \theta_2} \right]_{\theta=\theta_0}, \left[\frac{\partial f(t_i, \theta)}{\partial \theta_3} \right]_{\theta=\theta_0} \right],$$

$$x_0 = \begin{bmatrix} (\theta_1 - \theta_{10}) \\ (\theta_2 - \theta_{20}) \\ (\theta_3 - \theta_{30}) \end{bmatrix}.$$

That is, we now have a linear regression model. Therefore, the least-squares method for the estimates of x_0 is given by

$$\hat{x}_0 = (Z_0^{\mathrm{T}} Z_0)^{-1} Z_0^{\mathrm{T}} y_0. \tag{5}$$

Now since $x_0 = \theta - \theta_0$, we could define $\hat{\theta}_1 = \hat{x}_0 + \theta_0$ as revised estimates of θ. We may replace the revised estimates $\hat{\theta}_1$ in Eq. (4) and then produce another set of revised estimates, say $\hat{\theta}_2$ or $\hat{\theta}_3$, and so forth. This iteration continues until convergence is obtained, that is, until the increment is so small that there is no useful change in the elements of the parameter vector. When the procedure converges to a final vector of estimates, say $\hat{\theta}$, we can compute a residual mean square,

$$S^2 = \frac{\sum_{i=1}^{n} [y_i - f(t_i, \hat{\theta})]^2}{n - 2},$$

as an estimate of σ^2. The estimate of the asympotic covariance matrix of $\hat{\theta}$ is given as follows:

$$V(\hat{\theta}) = S^2 (Z^{\mathrm{T}} Z)^{-1}, \tag{6}$$

where Z is the matrix of partial derivatives defined previously, evaluated at the final-iteration least-squares estimate $\hat{\theta}$.

At the second stage the unobservable parameter, τ, in the between-individual model is replaced with the estimated parameter, $\hat{\tau}$. This replacement, however, introduces the estimation error δ, and Eq. (2) becomes

$$\hat{\tau} = \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \cdots + \gamma_m x_m + \varepsilon + \delta, \tag{7}$$

where δ is statistically independent of ε and is asymptotically normally distributed. Furthermore, we assume that $E(\delta) = 0$, $V(\delta) = \sigma_\tau^2$. Then, we can obtain that $\hat{\tau} \sim N(\gamma_0 + \gamma_1 x_1 + \cdots + \gamma_m x_m, \sigma^2 + \sigma_\tau^2)$. Finally, by replacing the γ's in Eq. (7) with the estimates γ's, $\hat{\tau}$ can be predicted in terms of x_1, K, x_m as

$$\hat{\hat{\tau}} = \hat{\gamma}_0 + \hat{\gamma}_1 x_1 + \cdots + \hat{\gamma}_m x_m. \tag{8}$$

The estimate $\hat{\tau}$ is based on the actual learning rate of the implementing TPM, while $\hat{\hat{\tau}}$ is based on the group characteristic such as the type of company and culture. Furthermore, the parameters of Y_c and Y_f can be obtained as in the above discussion.

In order to predict the OEE after implementing TPM at a future time t, one can use the following model:

$$\hat{Y}(t) = \hat{\hat{Y}}_c + \hat{\hat{Y}}_f(1 - \mathrm{e}^{-t/\hat{\hat{\tau}}}), \tag{9}$$

where the estimation of the parameters, Y_c and Y_f, is similar to that of the parameter $\hat{\hat{\tau}}$. In addition, one can estimate the expected time t when the OEE reaches a predetermined level (100-Y) using

$$\hat{t}_Y = \hat{\tau} \ln\left(1 - \frac{\hat{Y}(t) - \hat{\hat{Y}}_c}{\hat{\hat{Y}}_f}\right). \tag{10}$$

4. Illustrated examples

In order to illustrate the method suggested in this paper, several examples are presented using the TPM award data in Taiwan and Japan. Table 1 contains information regarding the series of the OEE found in 32 companies. The goals are to find the relationship between non-overall equipment effectiveness and concurrent characteristics of the company (company size, quality management and the types of manufacturing products, etc.). Then we can determine whether TPM was implemented in any company, to predict the learning rate in terms of concurrent characteristics of the company and to predict the OEE at a given time.

First, the estimation of the parameters in the within-individual model was obtained using non-linear Fit from JMP software [27]. The resulting $\hat{Y}_{ci}$'s, $\hat{Y}_{fi}$'s and $\hat{\tau}_i$'s with their corresponding company characteristics are summarized in Table 2.

Example 1. With respect to the estimated parameters, we want to see whether there exist difference between companies in Taiwan and those in Japan. The summarized statistics of the estimated parameters from these two groups of companies are shown as follows:

Parameter	Taiwan, $n_1 = 6$	Japan, $n_2 = 26$
Y_f/Y_c	$\bar{x}_1 = 0.791$ $s_1^2 = 0.372$	$\bar{x}_2 = 0.817$ $s_2^2 = 0.236$
τ	$\bar{x}_1 = 38.789$ $s_1^2 = 338.604$	$\bar{x}_2 = 47.943$ $s_2^2 = 285.592$

Since we have the p-value$= 0.125$ for the testing of the mean of the parameter Y_f/Y_c, we cannot reject the null hypothesis H_0: $\mu_1 = \mu_2$ at the 95% confidence level. That is, there is no strong evidence indicating that the mean of estimated dynamic gain from the companies in Taiwan is different from the mean of those in Japan. Since Taiwanese companies have adopted TPM programs and their philosophies from Japan, it is not surprising to find that the mean of OEE's learning indices from these two groups are not different. Also, since we have the p-value$= 0.455$ for the testing of the mean of the parameter τ, we cannot reject the null hypothesis H_0: $\mu_1 = \mu_2$ at the 95% confidence level. That is, the mean of estimated time constant from the companies in Taiwan is not different from the mean of those in Japan.

Example 2. With respect to the estimated parameters, we want to see whether there exists a difference between the companies of large size and the companies of small size. Here we define a firm with more than 500 employees as large sized, otherwise, small sized. The summarized statistics of the estimated learning index from these two types of companies are shown as follows:

Parameter	Large size companies, $n_1 = 16$	Small size companies, $n_2 = 16$
Y_f/Y_c	$\bar{x}_1 = 0.746$ $s_1^2 = 0.215$	$\bar{x}_2 = 0.926$ $s_2^2 = 0.301$
τ	$\bar{x}_1 = 41.119$ $s_1^2 = 328.569$	$\bar{x}_2 = 51.338$ $s_2^2 = 231.772$

Since we have the p-value$= 0.162$, we cannot reject the null hypothesis H_0: $\mu_1 = \mu_2$ at the 95% confidence level. That is, there is no strong evidence indicating that the mean of estimated dynamic gain from the larger companies is different from that of the small companies. These results also show that small plants as well as large plants can implement TPM and have the same maintenance performance. Further, it also implies that the state of the organization's resources may not limit a company's ability to implement TPM. Also, since we have the p-value$= 0.047$ for the testing of the mean of the parameter τ, we can reject the null hypothesis H_0: $\mu_1 = \mu_2$ at the 95% confidence level. That is, the mean of estimated time constant from the larger companies is different from the mean of these small companies.

Example 3. With respect to the estimated parameters, we want to see whether there exists a difference between the companies that are ISO 9000 certified and those that are not ISO 9000 certified. The summarized statistics of the estimated learning indices from these two types of companies are shown as follows:

Parameter	ISO 9000 certification, $n_1 = 16$	Non-ISO 9000 certification, $n_2 = 16$
Y_f/Y_c	$\bar{x}_1 = 0.997$ $s_1^2 = 0.342$	$\bar{x}_2 = 0.603$ $s_2^2 = 0.076$
τ	$\bar{x}_1 = 46.243$ $s_1^2 = 281.279$	$\bar{x}_2 = 46.213$ $s_2^2 = 338.575$

Table 1
The overall equipment effectiveness (%) observed in 32 companies

#1		#2		#3		#4		#5		#6		#7		#8	
Month	OEE	Month	OEE	Month	OEE	Month	OEE	Month	OEE	Month	OEE	Month	OEE	Month	OEE
0	57.6	0	55	0	65.6	0	65.9	0	47.0	0	70.2	0	45.3	0	53.0
6	63.1	6	66	6	71.4	6	72.0	6	52.0	6	74.9	3	51.6	6	59.0
12	68.2	12	71	12	75.4	12	75.0	12	63.0	12	78.3	6	61.0	12	64.0
18	72.0	18	77	18	78.8	18	78.0	18	66.0	18	81.7	9	65.4	18	69.0
24	77.7	24	82	24	81.3	24	81.0	24	70.0	24	84.2	12	73.9	24	73.0
30	80.6	30	86	30	84.3	30	82.0	28	78.6	30	86.4	15	76.5	30	77.0
36	82.8			36	88.0	36	85.0	29	78.7	36	87.3	17	77.4	36	81.0
42	84.2					42	87.3	30	78.5			22	80.8	42	84.0
48	85.0							31	77.8						
54	85.6							32	78.0						
60	85.7														
66	86.3														
#9		#10		#11		#12		#13		#14		#15		#16	
0	42.0	0	69.0	0	59.0	0	56.0	0	69.3	0	59.0	0	57.0	0	46.7
6	48.0	6	75.0	3	64.0	12	61.0	6	72.5	6	65.0	6	63.0	6	47.6
12	54.0	12	80.0	6	68.0	24	65.0	12	76.5	12	70.0	12	68.0	12	46.2
18	60.0	18	84.0	9	71.0	36	77.0	18	79.2	18	74.0	18	72.0	18	53.8
24	64.0	22	87.0	12	73.0	48	79.0	24	81.0	24	77.0	24	76.0	24	57.4
30	68.0	23	87.0	15	75.0	60	81.0	30	84.2	30	80.0	30	80.0	30	58.2
36	72.0	24	88.0	18	78.0	72	83.0	36	85.9	36	85.0	36	83.0	36	60.8
42	77.0			21	81.0	84	85.0					42	86.0	42	66.6
				24	83.0	96	86.0							48	60.0
				27	85.0	108	87.0							54	74.7
				30	86.0									60	77.5
														66	83.3
														72	85.5
														78	85.8
#17		#18		#19		#20		#21		#22		#23		#24	
0	52.0	0	74.9	0	72.0	0	37.4	0	63.1	0	43.2	0	62.0	0	77.1
3	55.6	6	78.0	3	73.2	9	50.5	6	69.5	6	50.0	6	67.0	12	81.0
6	58.7	18	82.0	6	74.3	21	62.0	12	74.5	12	56.2	12	71.0	24	86.2
9	61.7	22	82.5	9	75.3	33	72.0	18	78.0	18	62.6	18	74.0	36	87.6
12	64.4	24	82.8	12	76.3	40	77.5	24	80.0	24	67.7	24	77.0		
15	67.0	26	84.0	15	77.3	45	81.9	30	81.5	30	72.0	30	80.0		
18	69.5			18	78.2			36	82.5	36	76.1	36	83.0		
21	72.0			21	79.1					42	78.1	37	83.5		
24	74.0			24	79.9							38	84.0		
27	76.0			27	80.7							39	84.5		
30	78.0			28	81.0							40	85.0		
33	80.0			29	81.3										
35	82.0			30	81.6										
				31	81.8										
				32	82.0										
				33	82.2										
#25		#26		#27		#28		#29		#30		#31		#32	
0	68.0	0	73.9	0	60.0	0	56.6	0	59	0	62.0	0	68.7	0	40.0
6	73.2	6	78.0	6	67.0	6	63.5	12	71	6	67.0	6	72.2	6	47.0
12	77.7	12	81.8	12	72.0	12	69.8	24	79	12	71.0	12	75.5	12	53.0
18	81.7	18	85.3	18	76.0	18	74.9	36	85	18	74.5	18	78.8	18	58.5
24	85.2	24	88.3	24	79.5	24	79.5			24	77.7	22	80.4	24	63.5

Table 1 (*continued*)

#25	#26		#27		#28		#29	#30	#31		#32		
30	88.8	30	90.8	30	82.5	25	81.0	30	80.0	23	81.3	30	68.0
36	90.4	31	91.2	36	85.4	26	82.0	36	82.0	24	81.8	36	72.0
42	92.0	32	91.6			27	82.8	37	83.0	25	82.3	42	76.0
		33	92.0			28	83.4	38	83.4	26	81.8	48	79.2
		34	92.3					39	83.5	27	82.4		
										28	83.0		
										29	83.5		
										30	83.9		
										31	84.2		
										32	84.4		

Table 2
The estimation of the parameters with the company information

Company no.	$\hat{Y}_c$	$\hat{Y}_f$	$\hat{\tau}$	Employees	Sales	ISO-9000-certification	Award-year	Country
1	56.6	32.7	24.66	542	228.30	0	3	Taiwan
2	55.6	44.6	26.65	778	168.00	1	2.92	Taiwan
3	66.0	39.5	46.62	2036	648.00	1	3.92	Taiwan
4	66.5	28.8	34.92	662	160.00	1	2.92	Taiwan
5	46.5	92.7	72.55	450	152.00	1	5.17	Taiwan
6	70.1	23.9	27.39	617	180.00	1	3	Taiwan
7	44.2	47.0	13.67	164	2124.00	1	3	Japan
8	53.1	64.9	64.72	1065	717.00	1	4	Japan
9	42.0	18.0	72.28	71	350.00	0	3.16	Japan
10	69.0	39.7	37.40	132	24.90	1	2.83	Japan
11	59.7	43.3	31.54	313	124.00	0	2.83	Japan
12	54.4	37.2	48.87	404	116.00	0	3.83	Japan
13	69.2	33.5	52.00	328	315.00	1	3	Japan
14	59.4	51.8	55.45	193	29.80	0	3	Japan
15	57.2	53.6	54.62	474	107.00	0	3.17	Japan
16	47.5	55.8	68.01	523	360.00	0	4.83	Japan
17	52.2	63.1	56.33	1344	845.20	1	3	Japan
18	75.0	12.4	22.12	846	160.00	0	2.5	Japan
19	72.0	26.9	69.00	201	92.10	0	2.92	Japan
20	38.0	86.1	65.04	275	105.00	1	5.16	Japan
21	63.0	22.0	16.18	644	311.00	0	3.08	Japan
22	48.8	58.1	43.54	169	25.00	1	3.5	Japan
23	62.4	50.6	68.42	353	100.00	0	4.2	Japan
24	76.9	18.7	40.06	684	344.00	0	3.5	Japan
25	67.8	35.5	35.64	653	530.00	1	3.83	Japan
26	73.8	36.9	48.70	575	128.09	0	3.08	Japan
27	60.2	36.3	31.13	414	159.00	1	3	Japan
28	56.7	77.1	66.16	697	292.80	1	2.33	Japan
29	59.0	39.3	33.45	1932	1547.00	0	3.42	Japan
30	63.1	34.2	39.83	163	22.00	0	3.58	Japan
31	68.6	35.0	52.35	285	95.00	1	3.75	Japan
32	40.1	71.0	60.02	879	54.83	1	3.5	Japan

Since we have the p-value$= 0.010$, we can reject the null hypothesis H_0: $\mu_1 = \mu_2$ at the 95% confidence level. That is, there is strong evidence indicating that the mean of estimated dynamic gain from the companies with ISO 9000 certification is greater than that of the companies without ISO 9000 certification. McKone et al. [22] report that companies with strong quality programs should have strong autonomous and planned maintenance systems. There are several possible explanations for this result. First, TQM and TPM have similar support systems such as teamwork, skill development, and

Table 3
The results of the multiple linear regression for (a) $\hat{Y}_c$, (b) $\hat{Y}_f$ and (c) $\hat{\tau}$

Sources		df	SS	MS	F	p-value
(a)	Regression	4	1041.805	260.451	2.934	0.039
	Error	27	2396.765	88.769		
	Total	31	3438.570			
$R^2 = 0.303$ adj $R^2 = 0.200$						
		Coeff.	Standard error	t-statistic	p-value	
	Intercept	82.085	8.785	9.344	5.97E-10	
	Size	0.006	0.004	1.441	0.161	
	Sales	−0.007	0.004	−1.764	0.089	
	ISO 9000	−3.258	3.393	−0.960	0.346	
	Award year	−6.498	2.461	−2.641	0.014	
(b)	Regression	4	4751.481	1187.870	4.587	0.006
	Error	27	6992.125	258.968		
	Total	31	11743.606			
$R^2 = 0.405$ adj $R^2 = 0.316$						
		Coeff.	Standard error	t-statistic	p-value	
	Intercept	−9.188	15.005	−0.612	0.545	
	Size	−0.001	0.007	−0.104	0.918	
	Sales	−3.89E-04	0.007	−0.055	0.957	
	ISO 9000	14.513	5.795	2.504	0.019	
	Award year	13.542	4.203	3.222	0.003	
(c)	Regression	4	2850.467	712.617	3.011	0.036
	Error	27	6390.054	236.669		
	Total	31	9240.520			
$R^2 = 0.308$ adj $R^2 = 0.206$						
		Coeff.	Standard error	t-statistic	p-value	
	Intercept	8.976	14.345	0.626	0.537	
	Size	−1.66E-04	0.007	−0.025	0.980	
	Sales	−0.010	0.007	−1.465	0.154	
	ISO 9000	−0.198	5.540	−0.036	0.972	
	Award year	11.975	4.018	2.980	0.006	

process control. Once the systems are established they can be used to support both maintenance and quality improvement efforts. Second, high quality products are a result of good design, quality raw materials, reliable processes, and consistent equipment. The maintenance of the equipment is important to sustain the production of high quality products. As companies continue to improve their quality, they must also improve their maintenance delivery system and the overall equipment performance. Finally, some companies implement TPM programs to establish control of their operating environment. Once equipment performance is managed, companies are able to focus on quality improvement efforts. Our results also confirm that TQM and TPM programs are closely related based on the OEE's learning index performance. Also, since we have the p-value$= 0.498$ for the testing of the mean of the parameter τ, we cannot reject the null hypothesis H_0: $\mu_1 = \mu_2$ at the 95% confidence level. That is, the mean of estimated time constant from the companies with ISO 9000 certification is not different from the mean of those without ISO 9000 certification.

Example 4. Using Eq. (7) and the data in Table 2, the results of the multiple linear regression equation are shown in Tables 3(a–c). The estimated parameter of $\hat{Y}_c$, $\hat{Y}_f$ and $\hat{\tau}$

can be obtained as follows:

$$\hat{\hat{Y}}_c = 80.085 + 0.006 \times \text{size} - 0.007 \times \text{sales} - 3.258 \times \text{ISO} - 6.498 \times \text{award year},$$

$$\hat{\hat{Y}}_f = -9.188 - 0.001 \times \text{size} - 3.89 \times 10^{-4} \times \text{sales} + 14.513 \times \text{ISO} + 13.542 \times \text{award year},$$

$$\hat{\hat{\tau}} = 8.976 - 1.66 \times 10^{-4} \times \text{size} - 0.010 \times \text{sales} - 0.198 \times \text{ISO} + 11.975 \times \text{award year},$$

where size = employees, when the company has ISO 9000 certification then ISO = 1, otherwise ISO = 0, award year = years from the starting of the TPM program to winning the TPM award.

The assumptions of normality, homogeneity of variance-covariance matrices, linearity and multicollinearity are all satisfied for the above multiple linear regression models. We can use the above equations to obtain the estimated parameters, and then it can be easily used to predicting the OEE after implementing TPM at a future time t.

5. Conclusion

A random effect non-linear regression model called the Time Constant Model was used to formulate a prediction model for learning rate in terms of the size of company, sales, certified as ISO 9000 or not, and number of years from the starting of the TPM program to the award TPM. A two-stage analysis was employed to estimate the parameters. Using the approach of this study, one can determine the appropriate time for checking the performance of implementing TPM. Further, comparing the expected OEE, one can improve the maintenance policy. Our research results show that TQM and TPM programs are closely related. In addition, there is no strong evidence indicating that the mean of estimated learning index from the companies in Taiwan is different from that in Japan. Also, small plants as well as large plants can implement TPM and have the same maintenance performance. The approach of this research can help a company when it starts implementing the TPM program. The company can use this multiple linear equation to obtain the estimated learning index where the award year can be treated as the expected TPM award year. Then the expected OEE can be easily obtained and used to monitor the maintenance progress.

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