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Applying a Control Chart to the Learning Curve in TPM Adoption

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Abstract: Total productive maintenance (TPM) has been recognized as a useful methodology for maximizing equipment effectiveness and overall equipment effectiveness (OEE). Considering the multiplicity of availability, performance, and quality factors, it is an important performance metric for evaluating the adoption of TPM. In this study, a time constant learning curve model is used to formulate a forecasting model of OEE. An OEE forecast can be considered as a process and, therefore, can be managed by statistical process control (SPC). A control chart, i.e. an EWMA (exponentially weighted moving average) in this study, is easily used to monitor the forecast errors. If the forecast errors go out of the control limits, then something has happened to the TPM adoption and that the implementers should be notified and actions should be taken to ensure the successful adoption of the TPM. OEE data collected from three factories in Taiwan and Japan are used for illustration.

Keywords: Control chart, learning curve, overall equipment effectiveness, total productive maintenance.

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1. Introduction

In manufacturing industries, total productive maintenance (TPM) is one of the very important factory maintenance methodologies that are used throughout a product life cycle that try to optimize the effective use of production installations. This effectiveness can be measured in terms of the overall equipment effectiveness (OEE), which is a function of equipment availability, performance efficiency, and quality rate. In fact, the major key performance indicator for the TPM award (which is the first type of TPM award) is the OEE. In general, bestowal of this award requires at least 85% OEE for the application. (The second type of award is the TPM-continued award, and the third type is the TPM excellent award.) Over the years, TPM has been successfully implemented in Japan as well as other countries. The main concept of TPM is the enhancement of the overall effectiveness of factory equipment, and the provision of an optimal group organization approach for the accomplishment of system maintenance activities. However, very little progress has been made in predicting total equipment utilization in implementing TPM, although the merits of re-structuring organizations to better respond to maintenance challenges have been realized. In this study, we will focus on the adoption of TPM. A Time Constant Learning Curve model will be used to formulate a prediction model for the TPM learning rate.

Traditionally, the statistical process control (SPC) is used to monitor the stability of a process and to detect the non-stable factors (out-of-control activities). If assignable causes are present, then a change to the mean or variance of the process is indicated. (Note that the assignable causes can be unskilled workers, maintenance problems, and other factors.

These assignable causes can be controlled and reduced.) Normally, a process engineer or a production engineer will stop the production line, eliminate the assignable causes, and restart the production line. To achieve process control, control charts, such as Shewhart charts, CUSUM (cumulative summation), and EWMA (exponentially weighted moving average), are used extensively. SPC has proven to be effective for monitoring the stability of a process. We were inspired to develop an innovative approach that applies the use of a control chart, such as an EWMA, to a learning curve method (such as the time constant learning curve method) in the adoption of TPM. The model can be used to monitor the TPM adoption process, and easily foresee any deviations. The approach compares the collected performance indicator value (such as OEE) with the expected values, and the forecasting process can be continuously updated. The deviation (forecasting errors) provides prompt information to initiate any necessary managerial actions. Using this approach, it is possible to improve the maintenance policy and monitor the process TPM. The remainder of this paper is organized as follows. Section 2 reviews related TPM studies. Section 3 discusses the application of a control chart approach to the learning curve method. Three examples are presented in Section 4, which is followed by the conclusion in Section 5.

2. TPM and OEE

Total productive maintenance (TPM), a concept that was proposed by Seiichi Nakajima, has been beneficial to maintenance systems since 1971 [17]. Based on the definition of the Japanese Institute of Plant Maintenance (JIPM) (http://www.jipm.or.jp/en/home/), TPM is a system for equipment maintenance throughout its entire life cycle in all departments, such as planning, manufacturing, and maintenance. The word “total” in TPM has three different interpretations: (1) total effectiveness, including productivity, cost, quality delivery, safety, environment and health, and moral effectiveness; (2) total maintenance system, including maintenance prevention (MP) and maintainability improvement (MI); and (3) the total participation of all employees. Thus, in general, the goal of TPM is to increase the productivity of plant and equipment through the involvement of all employees in the organization in the various departments like production, maintenance, technical services, and stores. The most efficient way to maximize output is to eliminate the major causes that prevent the equipment from being effective. There are six major sources of loss of effectiveness in TPM. These include set-up and adjustment, equipment failure, reduced speed, idling and minor stoppages, reduced yield (from start up to stable production), and process defects. According to Nakajima [17], the first two are downtime losses – they reduce the availability of the equipment. The next two sources are considered as speed losses, which reduce system performance. The last two sources are categorized as defect losses due to the poor quality of the products produced.

To evaluate maintenance performance, overall equipment effectiveness (OEE), which evaluates manufacturing capability, can be used as a metric. Note that OEE is a function of equipment availability, performance efficiency, and quality. That is,

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

where

$$\textit{availability efficiency} = \frac{\textit{loading time} - \textit{downtime}}{\textit{loading time}},$$

$$performance\ \ efficiency = \frac{theoretical\ \ cycle\ \ time \times process\ \ amount}{operating\ \ time},$$

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

Hence, a manager can use the output of OEE to identify the causes of time losses and to reduce these losses.

There are many studies in which TPM has been used to solve problems. These studies mainly comprise case studies for TPM adoption and can be found in Blanchard [4], Cigolini and Turco [5], Hartmann [8], and Kaizen [11]. For example, Blanchard [4] and Cigolini and Turco [7] used TPM practices to recommend a continuous improvement approach in the operation and support of manufacturing systems. A general conceptual model, which outlines the distinctive features of the TPM approach in a specific industrial environment, is suggested in the study. Enkawa [6] and Miyake and Enkawa [14] integrated both total quality control (TQC) and TPM, while Miyake, Enkawa and Fleury [15] used JIT, TQC, and TPM to improve manufacturing systems performance. McKone, Schroeder and Cua [12] presented a theoretical framework to resolve the contextual issues in maintenance systems with TPM. Their study showed that the three proposed contexts – environmental (country, industry), organizational (equipment age, equipment type, company size, plant age, unionization), and managerial (just-in-time, total quality management, employee involvement) – influence the adoption of TPM by firms to different degrees. McKone, Schroeder and Cua [13] investigated the relationship between TPM and manufacturing performance (MP) in structural equation modeling. Their results show that there is a significant and positive indirect relationship between TPM and MP in Just-In-Time (JIT) implementation. Wang and Lee [22] proposed a random effect, non-linear regression model called the time constant model [21] to formulate a prediction model for the learning rate in terms of company size, sales, ISO 9000 certification, and TPM award year. In the study, it is possible to determine the appropriate checkpoints for the performance of implementing TPM. In addition, by comparing the expected OEE with that achieved, one can improve the maintenance policy and monitor the progress of OEE. A similar development, using a simple data envelopment analysis (DEA) method for efficiency evaluation in TPM, was adopted in [23]. The efficiency scores obtained from the DEA for 53 units are from the historical TPM awards in 1996-1999, and a multiple linear regression model was constructed to estimate the efficiency score of implementing TPM. A company can use this multiple linear regression model to obtain an estimated efficiency score to monitor their efficiency of implementing TPM.

3. Learning Curve in TPM

Learning curves have been studied and implemented extensively since the 1930s [24]. It is observed that the marginal cost decreased at a fixed rate (i.e., one minus the learning rate) when the cumulative production volume increased. That is, the learning curve function is a power function of the cumulative production volume. The learning rates are often assumed similar for similar products [9]. However, Argote and Epple [1] reported that the learning rates are actually significantly different between different organizations even when they are manufacturing the same products and using the same improvement measures of either productivity or product quality. (For detailed discussions on learning curve models, the reader can refer to [2, 7, 20 and 24].)

In the learning curve arena, a time constant learning curve model was found to be a good descriptor of many of the efforts toward industrial performance improvement [21]. The model develops a prediction function to monitor the improvement as a result of adopting TPM, based on collected field data, such as the value of OEE. The model for the time constant learning curve in TPM is given as follows:

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

where

$Y(t)$ = OEE (%) at time t,

Y_c = the initial level of OEE (%),

Y_f =the delivery data estimation,

Y_f / Y_c = the dynamic gain of OEE (%),

$Y_c + Y_f$ = the final level of OEE (%),

τ = the time constant (months) (a measure of how long it takes to achieve performance growth),

ε = the homoscedastical, serially noncorrelated error term with $E(\varepsilon) = 0$ and $V(\varepsilon) = \sigma_e^2$.

To estimate the parameters in Equation (1), a computer algorithm that is widely used for nonlinear regression is the linearization of the non-linear function followed by the Gauss-Newton iteration method of parameter estimation (Bates and Watts [3]). Note that linearization is accomplished by a Taylor series expansion of $f(t_i, \theta)$ about the point $\theta_0^T = [\theta_{10}, \theta_{20}, \theta_{30}] = [Y_{c0}, Y_{f0}, \tau_0]$ with only the linear terms retained. This yields

$$f(t_i, \theta) = f(t_i, \theta_0) + \sum_{j=1}^{3} \left[\frac{\partial f(t_i, \theta)}{\partial \theta_j} \right]_{\theta = \theta_0} (\theta_j - \theta_{j0})\,. \tag{2}$$

We can rewrite the above equation as follows

$$y_0 = Z_0 x_0 + \varepsilon\,, \tag{3}$$

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

$$\hat{x}_0 = (Z_0^T Z_0)^{-1} Z_0^T y_0\,. \tag{4}$$

Now, as $x_0 = \theta - \theta_0$, we can define $\hat{\theta}_1 = \hat{x}_0 + \theta_0$ as a revised estimate of θ. We then substitute the revised estimate $\hat{\theta}_1$ in Equation (3) and 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, there is no effective change in the elements of the parameter vector when the increment is too small. When the procedure converges to a final vector of estimates, say $\hat{\theta}$, we can compute a residual mean square, $S^2 = \sum_{i=1}^{n} [y_i - f(t_i, \hat{\theta})]^2 / (n-3)$, as an estimate of σ^2. The estimate of the asympotic covariance matrix of $\hat{\theta}$ is given as follows:

$$V(\hat{\theta}) = S^2 (Z^T Z)^{-1}, \tag{5}$$

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

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

$$\hat{Y}(t) = \hat{Y}_c + \hat{Y}_f (1 - e^{-t/\hat{\tau}}). \tag{6}$$

In addition, one can estimate the expected time t when the OEE reaches a predetermined level (100–Y) using

$$\hat{t}_Y = \hat{\tau} \ln \left(1 - \frac{\hat{Y}(t) - \hat{Y}_c}{\hat{Y}_f} \right). \tag{7}$$

For most manufacturing companies, OEE forecasting plays a key role in driving the production planning and scheduling and eventually influences the ability to meet customer expectations in quality. Here, OEE forecasting can be regarded as a process and the forecasting process is subject to statistical process control (SPC) (as illustrated in Figure 1). To make the forecast process useful, we require the forecast errors $e_t = Y(t) - \hat{Y}(t)$ to be small and centered around zero in statistical control. However, if the forecast errors become out of control (i.e., outside the upper control limit or the lower control limit), then it is an indication that something has happened to the TPM program and it is important that the implementers be alerted so that appropriate action can be taken. In addition, if many consecutive forecast errors are positive, then the learning rate should be changed. This indicates that a new learning cycle should be happening. Hence, the forecasting model of the learning curve should be updated and thus the learning improvement becomes dynamic. The concept of a learning cycle can be found in the work of Zangwill and Kantor [25], who presented a new theoretical framework for learning and making improvements based upon learning cycles. They proposed that each period should be considered as an opportunity to conduct a learning cycle. In each period an action is taken, say a change is made, a machine is adjusted, or a software program altered. Then, at the end of the period the data are examined to determine whether an improvement has occurred. This comprises the learning cycle. By repeatedly executing learning cycles, we can produce knowledge about which actions work, which do not, and how to improve the process.

4. Illustrative Examples

To examine the TPM adoption, this study uses the time constant learning curve to model the OEE data. Three examples from factories located in Taiwan and Japan with collected OEE, estimated OEE, and forecasted errors are provided (see Table 1). The estimation of the parameters in the time constant learning curve model was obtained using Nonlinear Fit from JMP software [10].

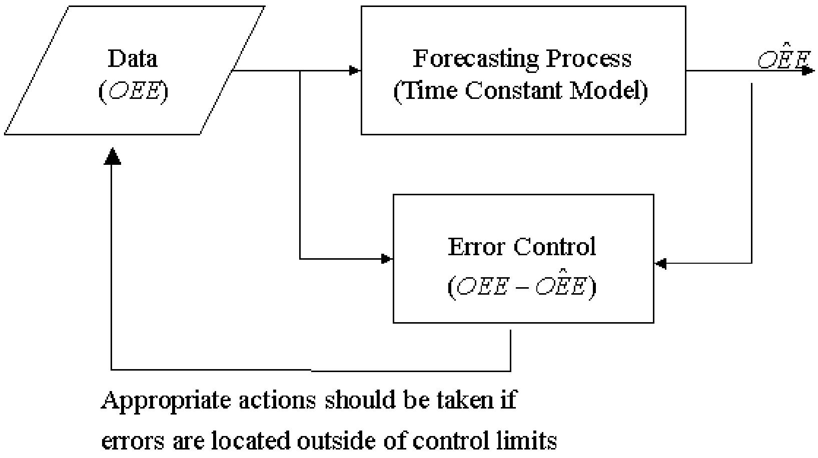

Figure 1. A forecasting error control loop.

This study will use an EWMA control chart to monitor the OEE data. Note that EWMA (exponentially weighted moving average) is a graphical and analytical tool used to determine whether a process is in a state of statistical control, and to detect a shift in the process mean [16]. Moreover, it is considered as a perfect, distribution-free procedure. For each monitoring point (e.g., monthly forecasting error of OEE for the factory), the one-step-ahead EWMA can be written as

$$\hat{e}_{t+1} = \lambda e_t + (1-\lambda)\hat{e}_t \, , \tag{8}$$

where λ is a smoothing constant and $\hat{e}_t$ is the forecast made at time t-1 for the error at time t. Typically, λ is between 0.05 and 0.25 depending on how dynamic the process is. A good rule of thumb is to take smaller values of λ when detecting smaller shifts. For this control statistic, the control limits in Equation (8) are

$$\mu_0 \pm L\sigma_e \sqrt{\frac{\lambda}{2-\lambda}[1-(1-\lambda)^{2t}]} \, , \tag{9}$$

where $\sqrt{\lambda/(2-\lambda)}\sigma_e = \sigma_{\hat{e}}$ is the asymptotic standard deviation of $\hat{e}$ under the assumption that the expected errors are independent. The factor L is the half width of the control limits. The EWMA control chart is very effective against small process shifts. The goal of monitoring changes adversely affecting the TPM's effectiveness is to activate a change process as early as possible. Ideally, the quality control procedure should activate a process before the data can be visualized as a change in the underlying rates.

Example 1. The Gauss-Newton iteration method was used to estimate the parameters in the Equation (1) for Factory A data in Table 1 using the starting values $[\theta_{10}, \theta_{20}, \theta_{30}] = [Y_{c0}, Y_{f0}, \tau_0] = [57.6, 10, 20]$. The objective function was converged at the 8th iteration. The OEE results of the time constant learning curve model for Factory A are given as follows:

$$\hat{Y}(t) = 53.5319 + 41.1957 \times (1 - e^{-t/24.5335}) \, ,$$

with the corresponding mean square error (MSE) = 6.4040 and root mean square error (RMSE) = 2.5306. The solid line in Figure 2 represents the time constant learning curve for Factory A. (Note that 100% of OEE means 100% of equipment utilization, which is not possible. Therefore, the forecasting value of the time constant learning curve cannot exceed 100%.) The EWMA control chart, with $\lambda = 0.2$ and $L = 2.7$, for the data for Factory A is shown in Figure 3. The many points at which significant changes in the forecasting error rates occurred can be seen. For example, the errors for the months between 0 and 20 and the months between 40 and 46 are located outside of either the LCL or the UCL. These months are considered as the out-of-control periods. Thus, the necessary actions should be taken during these periods.

Example 2. Using the same procedures in Example 1, the objective function was converged at the 10th iteration. The OEE results of the time constant learning curve model for Factory B are given as follows:

$$\hat{Y}(t) = 65.9218 + 21.0327 \times (1 - e^{-t/17.5257}),$$

with MSE = 5.6617 and RMSE = 2.3794. The solid line in Figure 4 represents the Time Constant Learning Curve for Factory B. The EWMA control chart, with $\lambda = 0.2$ and $L = 2.7$, for the data for Factory B is shown in Figure 5. The many points at which significant changes in the forecasting error rates occurred can be seen. For example, the errors in the months between 12 and 20 and in the months between 34 and 48 are located outside of either the LCL or the UCL. These months are considered as the out-of-control periods. Thus, the necessary actions should be taken during these periods.

Example 3. Using the same procedures in Example 1, the objective function was converged at the 4th iteration. The OEE results of the time constant learning curve model for Factory C are given as follows:

$$\hat{Y}(t) = 81.7570 + 18.3003 \times (1 - e^{-t/30.9813}),$$

with MSE = 2.7389 and RMSE = 1.6550. The solid line in Figure 6 represents the time constant learning curve for Factory C. The EWMA control chart, with $\lambda = 0.2$ and $L = 2.7$, for the data for Factory C is shown in Figure 7. The many points at which significant changes in forecasting error rates occurred can be seen. For example, the errors in the months between 5 and 7 and in the months between 20 and 26 are located outside of either the LCL or the UCL. These months are considered as the out-of-control periods. Thus, the necessary actions should be taken during these periods.

Moreover, the learning rates and the final stage of the OEE value can also be observed from the estimated parameters of the time constant learning curve model for these three factories. From Equation (1), we have $\hat{Y}(t) = \hat{Y}_c + \hat{Y}_f(1 - e^{-(t/\hat{\tau})}) = (\hat{Y}_c + \hat{Y}_f) - \hat{Y}_f e^{-t/\hat{\tau}}$. As $\hat{Y}_c + \hat{Y}_f$ is a constant value and let $\dot{Y}(t) = -\hat{Y}_f e^{-(t/\hat{\tau})}$, then we have $d\ln(\dot{Y}(t))/dt = d(-\ln(\hat{Y}_f) + t/\hat{\tau})/dt = 1/\hat{\tau}$. If the estimated value of τ is large, then the value of $\ln(\dot{Y}(t))$ is small, that is, the learning rate is small. Additionally, the estimated value of $Y_c + Y_f$ for the final stage of the OEE value is thought of as the performance measure for the TPM adoption. Comparing factories A, B, and C, we have $\hat{\tau}_C > \hat{\tau}_A > \hat{\tau}_B$ and $(\hat{Y}_c + \hat{Y}_f)_C > (\hat{Y}_c + \hat{Y}_f)_A > (\hat{Y}_c + \hat{Y}_f)_B$. That is, we find that Factory B has the best learning rate, but the final stage of OEE value is the worst. In contrast, Factory C has the best final stage of the OEE value, but the worst learning rate. Using this approach, one can use EWMA to monitor the learning rate of the TPM adoption so that the out-of-control activities can be identified and highlighted. Therefore, the adoption of TPM in factories B and C can be improved in the earlier stages.

Table 1. The collected OEE (%), estimated OEE, and forecasted errors, in three factories.

	Factory-A			Factory-B			Factory-C		
Month	*OEE*	$\hat{OEE}$	error	*OEE*	$\hat{OEE}$	error	*OEE*	$\hat{OEE}$	error
1	59.80	55.18	4.62	70.34	67.09	3.25	83.90	82.34	1.56
2	64.00	56.76	7.24	69.77	68.19	1.58	87.60	82.90	4.70
3	64.50	58.27	6.23	67.74	69.23	-1.49	84.40	83.45	0.95
4	60.20	59.73	0.47	72.92	70.21	2.71	82.80	83.97	-1.17
5	64.70	61.13	3.57	73.87	71.14	2.73	79.50	84.48	-4.98
6	59.00	62.47	-3.47	72.13	72.02	0.11	79.90	84.98	-5.08
7	64.60	63.76	0.84	72.00	72.85	-0.85	85.10	85.46	-0.36
8	61.10	64.99	-3.89	73.19	73.63	-0.44	84.90	85.92	-1.02
9	63.50	66.18	-2.68	73.16	74.37	-1.21	86.70	86.37	0.33
10	61.60	67.32	-5.72	73.37	75.07	-1.70	86.50	86.81	-0.31
11	61.00	68.42	-7.42	72.32	75.73	-3.41	88.10	87.23	0.87
12	66.10	69.47	-3.37	72.89	76.35	-3.46	87.20	87.63	-0.43
13	71.80	70.48	1.32	75.09	76.94	-1.85	86.70	88.03	-1.33
14	68.60	71.45	-2.85	75.81	77.49	-1.68	86.60	88.41	-1.81
15	67.50	72.38	-4.88	76.67	78.02	-1.35	88.80	88.78	0.02
16	67.90	73.27	-5.37	74.42	78.51	-4.09	88.10	89.14	-1.04
17	67.30	74.13	-6.83	77.76	78.98	-1.22	91.20	89.49	1.71
18	68.60	74.95	-6.35	77.68	79.42	-1.74	91.80	89.82	1.98
19	79.10	75.74	3.36	80.08	79.84	0.24	92.60	90.15	2.45
20	73.10	76.50	-3.40	79.60	80.24	-0.64	93.00	90.46	2.54
21	79.40	77.22	2.18	80.72	80.61	0.11	93.90	90.77	3.13
22	78.20	77.92	0.28	81.83	80.96	0.87	93.40	91.06	2.34
23	76.00	78.60	-2.60	82.27	81.29	0.98	93.40	91.35	2.05
24	79.90	79.24	0.66	81.87	81.61	0.26	92.20	91.62	0.58
25	81.00	79.86	1.14	82.87	81.90	0.97	93.00	91.89	1.11
26	84.50	80.45	4.05	81.43	82.18	-0.75	93.90	92.15	1.75
27	82.40	81.02	1.38	80.09	82.45	-2.36	90.20	92.40	-2.20
28	83.80	81.57	2.23	81.19	82.70	-1.51	90.80	92.64	-1.84
29	84.40	82.10	2.30	82.68	82.93	-0.25	92.00	92.88	-0.88
30	84.20	82.60	1.60	83.87	83.16	0.71	93.10	93.11	-0.01
31	82.00	83.08	-1.08	86.11	83.37	2.74	92.20	93.33	-1.13
32	85.90	83.55	2.35	85.07	83.57	1.50	93.60	93.54	0.06
33	83.60	84.00	-0.40	85.64	83.75	1.89	93.70	93.75	-0.05
34	86.00	84.42	1.58	85.36	83.93	1.43	94.90	93.95	0.95
35	88.60	84.84	3.76	85.56	84.10	1.46	93.70	94.14	-0.44
36	86.10	85.23	0.87	87.74	84.26	3.48	93.60	94.33	-0.73
37	84.30	85.61	-1.31	87.39	84.41	2.98	93.50	94.51	-1.01
38	87.90	85.97	1.93	87.71	84.55	3.16	94.70	94.69	0.01
39	87.80	86.32	1.48	88.19	84.68	3.51	94.90	94.86	0.04
40	90.30	86.66	3.64	85.81	84.81	1.00	93.90	95.03	-1.13
41	89.70	86.98	2.72	86.34	84.93	1.41	94.90	95.19	-0.29
42	91.80	87.29	4.51	87.61	85.04	2.57	95.60	95.34	0.26
43	89.40	87.59	1.81	88.71	85.15	3.56	96.70	95.49	1.21
44	89.30	87.87	1.43	86.55	85.25	1.30	94.90	95.63	-0.73
45	90.90	88.15	2.75	86.63	85.34	1.29	95.30	95.78	-0.48
46	91.70	88.41	3.29	86.36	85.43	0.93	93.80	95.91	-2.11
47	92.20	88.66	3.54	86.28	85.51	0.77	93.10	96.04	-2.94
48	91.40	88.90	2.50	87.02	85.59	1.43	95.80	96.17	-0.37
49	89.20	89.14	0.06	86.50	85.67	0.83	96.10	96.29	-0.19
50	87.90	89.36	-1.46	85.11	85.74	-0.63	97.00	96.41	0.59
51	87.80	89.57	-1.77	86.72	85.81	0.91	97.90	96.53	1.37
52	90.30	89.78	0.52	86.12	85.87	0.25	97.70	96.64	1.06
53	89.70	89.98	-0.28	84.46	85.93	-1.47	94.00	96.75	-2.75
54	91.80	90.17	1.63	85.78	85.99	-0.21	98.10	96.85	1.25
55	89.40	90.35	-0.95	86.83	86.04	0.79	97.30	96.96	0.34

Table 1. Continued.

56	89.30	90.52	-1.22	86.98	86.09	0.89	96.70	97.06	-0.36
57	90.90	90.69	0.21	87.56	86.14	1.42	99.00	97.15	1.85
58	91.70	90.85	0.85	87.69	86.19	1.50	97.50	97.24	0.26
59	92.20	91.01	1.19	88.96	86.23	2.73	97.70	97.33	0.37
60	91.40	91.16	0.24	89.56	86.27	3.29	96.30	97.42	-1.12
61	89.80	91.30	-1.50	83.42	86.31	-2.89	95.10	97.50	-2.40
62	91.40	91.44	-0.04	83.55	86.34	-2.79	96.40	97.58	-1.18
63	91.50	91.57	-0.07	81.00	86.38	-5.38	96.90	97.66	-0.76
64	91.80	91.69	0.11	80.91	86.41	-5.50	97.30	97.74	-0.44
65	92.10	91.82	0.28	79.57	86.44	-6.87	96.60	97.81	-1.21
66	91.10	91.93	-0.83	81.33	86.47	-5.14	96.70	97.88	-1.18
67	90.90	92.04	-1.14	83.90	86.49	-2.59	98.20	97.95	0.25
68	92.30	92.15	0.15	83.34	86.52	-3.18	98.80	98.02	0.78
69	92.20	92.25	-0.05	85.67	86.54	-0.87	98.90	98.08	0.82
70	92.70	92.35	0.35	87.63	86.57	1.06	99.80	98.15	1.65
71	92.60	92.45	0.15	88.42	86.59	1.83	98.80	98.21	0.59
72	92.60	92.54	0.06	87.69	86.61	1.08	99.90	98.27	1.63
73	90.30	92.63	-2.33				98.60	98.32	0.28
74	91.80	92.71	-0.91				99.90	98.38	1.52
75	92.80	92.79	0.01				98.70	98.43	0.27
76	92.80	92.87	-0.07						
77	92.30	92.94	-0.64						
78	89.50	93.01	-3.51						
79	91.50	93.08	-1.58						
80	90.70	93.15	-2.45						
81	93.80	93.21	0.59						
82	93.90	93.27	0.63						
83	94.10	93.33	0.77						
84	93.90	93.39	0.51						
85	92.80	93.44	-0.64						
86	93.90	93.49	0.41						
87	93.90	93.54	0.36						
88	94.00	93.59	0.41						
89	93.80	93.63	0.17						
90	94.10	93.68	0.42						
91	94.60	93.72	0.88						
92	93.80	93.76	0.04						
93	94.40	93.80	0.60						
94	94.60	93.83	0.77						
95	93.80	93.87	-0.07						
96	93.20	93.90	-0.70						
97	93.20	93.94	-0.74						
98	93.90	93.97	-0.07						
99	93.90	94.00	-0.10						
100	93.80	94.03	-0.23						
101	93.00	94.06	-1.06						
102	94.40	94.08	0.32						
103	93.60	94.11	-0.51						
104	93.90	94.13	-0.23						
105	93.30	94.16	-0.86						
106	91.30	94.18	-2.88						
107	89.80	94.20	-4.40						
108	94.80	94.22	0.58						

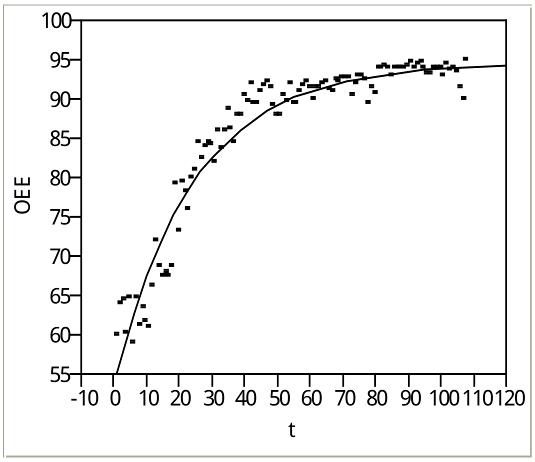

Figure 2. Measured OEE with time constant learning curve for factory A.

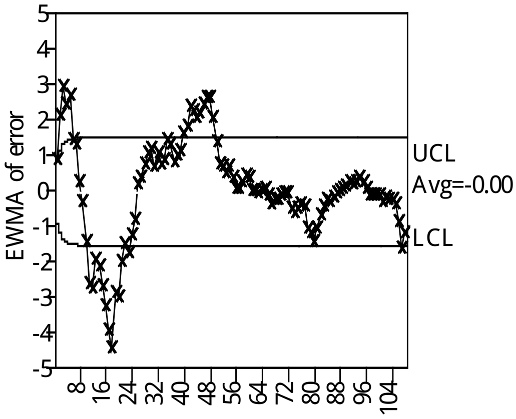

Figure 3. The EWMA control chart for factory A.

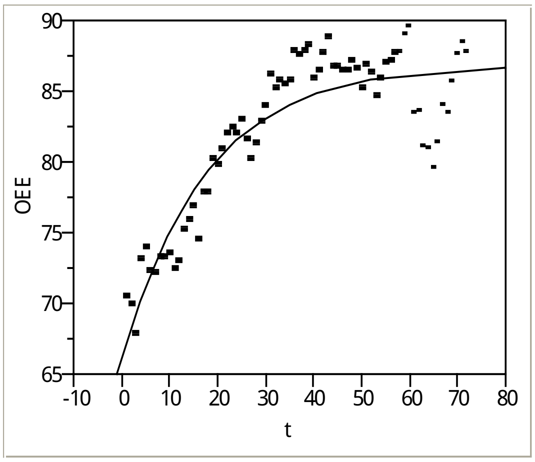

Figure 4. Measured OEE with time constant learning curve for factory B.

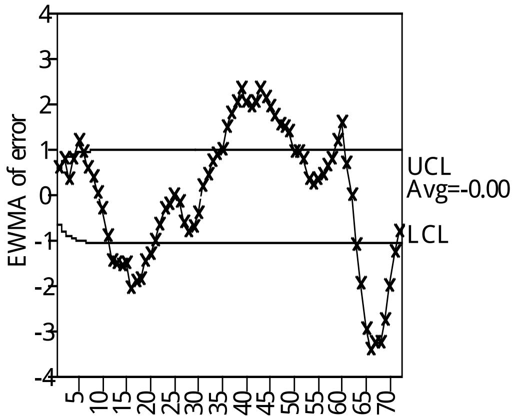

Figure 5. The EWMA control chart for factory B.

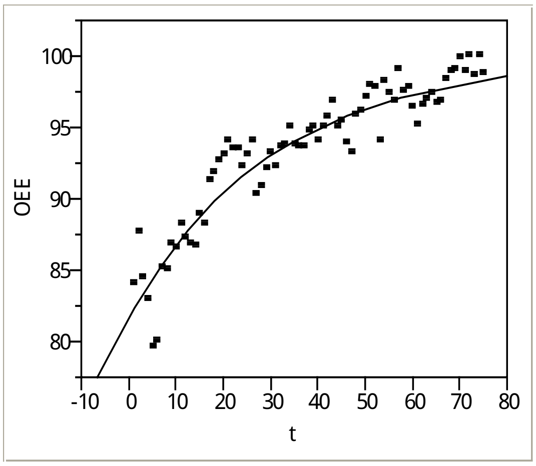

Figure 6. Measured OEE with time constant learning curve for factory C.

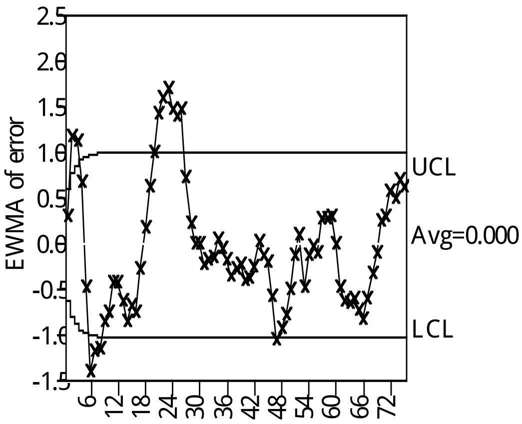

Figure 7. The EWMA control chart for factory C.

5. Conclusion

TPM has been recognized as an important methodology to improve equipment effectiveness and OEE is an important metric for TPM adoption. The forecast of OEE can be used to indicate the success or failure of the TPM adoption during a given period. In this study, the time constant learning curve model was used to formulate the forecasting model for the OEE. OEE forecasting can be considered as a process and, therefore, can be managed by a statistical process control (SPC) mechanism, such as EWMA. For the forecast process to be useful, we require the forecast errors $e_t = Y(t) - \hat{Y}(t)$ to be small, centered around zero, and under statistical control. However, if the forecast errors go outside of the control limits, then something has happened to the TPM adoption and the implementers should be notified to take appropriate action. To illustrate the procedure, OEE data were collected from three factories in Taiwan and Japan. It was found that the present approach makes it possible to monitor the performance of TPM adoption through the control chart.

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