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Evaluating the Efficiency of Implementing Total Productive Maintenance

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ABSTRACT *Total Productive Maintenance (TPM) has been widely recognized as a strategic weapon for improving manufacturing performance. This has also been successfully implemented in many organizations. The evaluation of TPM efficiency can assist factories in improving their operations across a variety of dimensions. In particular, it aids factories in monitoring their performance in comparison with other factories. Effective benchmarks of high performance and efficient cluster are identified for improving the factories in the other groups. Here, Data Envelopment Analysis (DEA) is used to evaluate the efficiency score for when the utility function considers its many attributes. A prediction model by the multiple regression method is obtained. This regression equation can be used to obtain the expected efficiency score for checking the performance of implementing TPM. Finally, the proposed methodology can identify a peer group of efficient factories against which to benchmark. The actual improvement process may involve identifying the operating practices and procedures of the benchmark factories and engaging in re-engineering programs.*

KEY WORDS: Total Productive Maintenance, efficiency, data envelopment analysis

Introduction

In 1971, Nakajima (1988) introduced the concept of Total Productive Maintenance (TPM) which is a productive maintenance carried out by all employees through small group activities. Since then, TPM methods and techniques have been successfully implemented in Japan and also employed outside Japan. Inherent within the TPM concepts are the ideas of enhancing the overall effectiveness of factory equipment, and providing an optimal group organizational approach to 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. For example, the TPM Prize for successful

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implementation of TPM was awarded to 1276 factories in the past 30 years between 1971 and 2000. It is believed that while many successes have been achieved in structuring organizations to respond better to the maintenance challenge, very little progress has been made related to the efficiency evaluation in TPM.

The motivation for this research primarily stems from the following issues associated with the TPM implementation in industries. First, efficiency management is concerned with a fuller utilization of available inputs to achieve an optimum mix of outputs within the boundaries of feasibility in operations. Both capacity utilization and quality of output are relevant parameters in the measurement of productivity of any decision-making unit. Secondly, in most factories, the evaluation of TPM performance is based on overall equipment effectiveness (OEE) and other factors such as housekeeping cross-training, teams, and operation involvement. However, the financial impact should be included in this type of evaluation. Thus, the performance evaluation should be based on multiple inputs and multiple outputs. Finally, in order for factories to know their relative efficiency among those TPM Prize factories, an objective and comprehensive method is required. Since the evaluation involves multiple inputs and multiple outputs, it can be thought of as a multi-criteria decision problem.

Data Envelopment Analysis (DEA) can assist with such problems as described above. DEA has also gained popularity over the last several years. Several types of these applications can be found in Charnes *et al*. (1994). This article utilizes Data Envelopment Analysis (DEA), a non-parametric multi-factor productivity analysis tool, which effectively considers multiple input and output measures in evaluating a single, composite score, referred to as efficiency. In the process, some units achieves 100% efficiency and are referred to as the relatively efficient units, whereas other units with efficiency ratings of less than 100% are referred to as inefficient units. It allows for identifying appropriate benchmarks for poorly performing factories in TPM that are potentially important to monitor their performance for allocating the resources or re-planning the goals such as OEE. In addition, the multiple linear regression model was used to formulate the regression equation for predicting the efficiency score in terms of the TPM award months, the number of employees, the ratio of spending TPM to sales, the sales growth and OEE. Using the approach of this study, it is easy to determine the efficiency score of implementing total productive maintenance based on those TPM Prize factories.

This article is divided into the following sections. Several related literatures are reviewed in the next section, followed by the data descriptions and analysis results. Managerial implications and prediction model are presented in the fourth section, and the conclusions are made in the final section.

Literature Review

Total Productive Maintenance

Total Productive Maintenance, proposed by Seiichi Nakajima, has been widely applied for its benefits to the maintenance delivery system since 1971 (Nakajima, 1988). The Japanese Institute of Plant Maintenance (JIPM) defined TPM as a system of maintenance covering the entire life of the equipment in every division including planning, manufacturing, and maintenance. 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, and morals); (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 with the involvement of all employees in the organization, who may belong to various departments such as production, maintenance, technical services and stores. To maximize output, the most efficient way is to eliminate causes, the so-called *six big losses* in TPM that reduce equipment effectiveness. (The 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, overall equipment effectiveness (OEE) is used as a metric to evaluate the manufacturing capability. OEE is a function of equipment availability, performance efficiency, and quality. That is,

$$\mathrm{OEE} = (\mathit{availability}) \times (\mathit{performance\ efficiency}) \times (\mathit{quality\ rate})$$

where

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

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

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

An 85% OEE is considered as 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 the major objectives for mostly firms when implementing TPM. In addition, other factors such as housekeeping cross-training, teams, and operation involvements are also used as the measures for the TPM Prize criterion. Typically, it takes an average of three and half years from introduction of TPM to achieve prize-winning results.

Most articles have presented TPM improvement activities in plants and, based on case studies, suggest implementation procedures (Blanchard, 1997; Cigolini & Turco, 1997; Hartmann, 1992; Kaizen, 1997; Patterson *et al*., 1996; Suzuki, 1992). Blanchard (1997) presented some design analysis/evaluation tools that can be used, and he also recommended an approach for the continuous improvement of manufacturing systems in terms of operation and support. Cigolini & Turco (1997) presented some TPM practices in the manufacturing industry. A more general conceptual model capable of outlining the distinctive features of each TPM approach when facing a specific industrial environment is suggested. The detailed implementation procedures and case studies can be found in Hartmann (1992), Kaizen (1997), Patterson *et al*. (1996) and Suzuki (1992). Miyake & Enkawa (1999) developed in-depth systematized comparisons under the perspective of analyzing mutual complementary between Total Quality Control (TQC) and TPM. Miyake *et al*. (1995) studied the application of JIT, TQC and TPM paradigms to improve manufacturing systems performance. McKone *et al*. (1999) proposed a theoretical framework by testing how the contextual issues affect the maintenance system of firms when implementing TPM. Their studies show that the three proposed 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) – influences TPM adoptions in firms at different levels. McKone *et al*. (2001) investigated the relationship between TPM and manufacturing performance (MP) through structural equation modeling. The results show that there is a significant and positive indirect relationship between TPM and MP through Just-In-Time (JIT) practices. Wang & Lee (2001) proposed a random effect non-linear regression model called the Time Constant Model to formulate a prediction model for the learning rate in terms of company size, sales, ISO 9000 certification and TPM award year. 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.

Data Envelopment Analysis

Charnes *et al*. (1978) developed the Data Envelopment Analysis (DEA) approach based on the concept of technical efficiency of Farrel (1957). DEA, in essence, is a linear programming technique that converts multiple inputs and outputs into a scale measure of efficiency. It is also a decision-making technique that has been widely used for performance analysis in public and private sectors. By using DEA one would be able to compare a group of decision-making units to identify relatively inefficient units; measure the magnitude of the inefficiencies; compare the inefficient with the efficient ones and discover ways to reduce the inefficiencies. Some works of DEA development can be found in Banker *et al*. (1984) and Charnes *et al*. (1994). In addition, Charnes *et al*. (1978) presented several of these types of application in their DEA book. The CCR DEA model by Charnes *et al*. (1978) yields an objective evaluation of overall efficiency via the optimal value of the ratio form, as obtained from the data without requiring a priori specification of weights and/or explicit delineation of assumed functional forms of relations between input and outputs. In addition, in some industries the Decision Making Units (DMUs) may be given fixed resources and asked to produce as much output as possible. In this case, an output orientation would be appropriate. However, this assumption is not suitable for this study. Thus, we chose the CCR input orientation model. If the BCC input orientation model by Banker *et al*. (1984) is selected, the results of the efficiency scores will be different from the CCR input orientation model, because the BCC input orientation model distinguishes between technical and scale inefficiencies by estimating pure technical efficiency at the given scale of operation. A brief description of the CCR model is given as follows:

First, the definitions of variables are listed as follows.

Let E_k with $k = 1, 2, \ldots, N$, be the efficiency ratio of decision-making unit k, where N is the total number of units being evaluated.

Let u_j with $j = 1, 2, \ldots, S$, be a coefficient for output j, where S is the total number of output variables being considered. The variable u_j is the measure of the relative decrease in efficiency with each unit reduction of output value.

Let v_i with $i = 1, 2, \ldots, M$, be a coefficient for output i, where M is the total number of input variables being considered. The variable v_i is the measure of the relative increase in efficiency with each unit reduction of input value.

Let Y_{jk} be the number of observed units of output j generated by unit k during one time period.

Let X_{ik} be the number of actual units of input i generated by unit k during one time period.

Mathematically, the objective is to find the set of coefficient us associated with each output and with vs associated with each input that will give the evaluated DMU the highest possible efficiency. That is,

$$Max\ E_k = \frac{\sum_{j=1}^{S} u_j y_{jk}}{\sum_{i=1}^{M} v_i x_{ik}} \tag{1}$$

subject to

$$\frac{\sum_{j=1}^{S} u_j y_{jk}}{\sum_{i=1}^{M} v_i x_{ik}} \leq 1 \quad k = 1, 2, \ldots, N$$

$$u_j, v_i \geq 0 \quad \forall j, i$$

To solve this fractional linear programming model use standard linear programming software that requires reformulating the model as

$$Max\ E_k = \sum_{j=1}^{S} u_j y_{jk} \tag{2}$$

subject to

$$\sum_{i=1}^{M} v_i x_{ik} = 1$$

$$\sum_{j=1}^{S} u_j y_{jk} - \sum_{i=1}^{M} v_i x_{ik} \leq 0, \quad k = 1, 2, \ldots, N$$

$$u_j, v_i \geq 0 \quad \forall j, i$$

Since the number of DMUs is generally larger than the total number of inputs and outputs, the computational burden can be reduced by solving the dual of model 2. Hence, the dual formulation of equation (2) is

$$Min\ \theta \tag{3}$$

subject to

$$\sum_{k=1}^{N} \lambda_k x_{ik} \leq \theta x_{ik}, \quad i = 1, 2, \ldots, M$$

$$\sum_{k=1}^{N} \lambda_k y_{jk} \geq y_{jk}, \quad j = 1, 2, \ldots, S$$

$$\lambda_k \geq 0 \quad \forall k$$

where θ represents the efficiency score of unit k; λ represents the dual variables that identify the benchmarks for inefficient units.

Data Descriptions and Analysis Results

Data Descriptions

A total of 279 factories with the TPM award during 1996–1999 were mailed in order to collect the data. However, only 53 factories provided the complete information, corresponding to a 19% return rate. For each factory, data were either obtained on three inputs related to investments or planning the TPM award and four outputs related to financial performance, availability, performance efficiency and quality rate. The DEA methodology was then applied to evaluate the relative efficiency of the 53 factories based on these three inputs and four outputs. The original data for the study are summarized in Table 1. Specifically, the three inputs related to investments or planning in TPM included in this study are: (1) x_1: the months from the start of the TPM program to winning the TPM award; (2) x_2: the number of employees in the factory; and (3) x_3: implementing TPM budget as a percentage of sales. The first measure relates to the plant's willingness to spend the time for the TPM award to be obtained. The second measure corresponds to the total number of employees in each factory. The last measure relates to the spending of TPM. Specifically, the four outputs related to the sales growth from the beginning of TPM to the obtaining of the TPM award, and the three values in the OEE are: (1) y_1: the sales growth from the beginning of TPM to the obtaining of the TPM award; (2) y_2: the availability; (3) y_3: the performance efficiency; and (4) y_4: the quality rate.

These inputs and outputs are in differing units. Although DEA can successfully process inputs/outputs on differing numeric scales via weighting, standardization is performed on three inputs and four outputs so that weighting schemes can be kept as universal as possible. To explain the standardization process, the following definitions are provided:

O_{ij} = the value of variable j for factory i,
$\bar{O}_j$ = the mean value for variable j across all factories,
$\hat{\sigma}_j$ = the standard deviation of the value for variable j across all factories,
Z_{ij} = the number of standard deviations factory i is above or below the mean for variable j (Z-scores).
RZ_{ij} = Z-scores re-scaled from zero.

Table 1. The original data of the 53 factories

Factory #	x1	x2	x3	y1	y2	y3	y4
1	46	190	0.3	0.100	68.80	98.18	100.00
2	68	130	0.7	4.619	98.00	74.00	96.00
3	35	163	0.5	0.357	69.00	98.60	99.90
4	36	770	1.02	0.099	96.12	65.45	99.99
5	36	596	0.88	0.033	98.00	100.00	99.00
6	30	1200	0.32	0.016	90.90	100.00	96.70
7	74	892	0.41	0.186	89.60	96.09	100.00
8	42	550	0.5	0.318	94.00	92.00	99.90
9	62	192	1.4	0.023	97.23	89.15	98.60
10	52	830	0.58	−0.012	81.00	95.91	96.50
11	49	160	0.8	−0.045	90.60	95.90	96.90
12	40	873	0.7	0.075	94.60	96.70	93.10
13	60	660	0.84	−0.076	96.10	98.70	96.30
14	47	150	0.09	0.217	90.20	94.80	100.00
15	40	1201	0.8	0.262	94.40	94.50	99.93
16	33	1070	1.2	−0.077	93.50	91.90	97.50
17	27	450	1.11	0.147	92.00	91.00	99.50
18	48	200	1.02	0.135	97.80	83.20	99.90
19	43	562	1.5	−0.025	91.16	89.82	99.89
20	39	260	1.4	−0.021	96.40	92.40	98.40
21	52	675	0.84	−0.005	95.50	95.10	99.80
22	32	480	1.13	0.040	81.30	80.50	99.00
23	46	780	0.81	0.118	89.90	99.60	100.00
24	35	439	0.74	0.285	94.61	93.74	98.96
25	47	229	1.4	0.011	84.80	98.50	99.40
26	42	1131	0.43	0.179	91.30	90.40	99.00
27	30	425	1.225	−0.018	79.50	98.09	96.50
28	55	208	0.88	0.111	99.20	100.00	100.00
29	35	52	1.21	−0.394	83.80	76.90	99.00
30	36	600	0.745	0.555	91.03	82.44	99.35
31	41	336	0.758	0.368	85.00	100.00	100.00
32	41	405	1.6	−0.155	90.50	98.40	96.70
33	79	860	1.3	−0.025	89.40	93.80	98.40
34	42	196	0.57	−0.067	84.60	99.80	99.90
35	24	600	0.94	−0.125	89.40	94.70	97.80
36	31	343	0.77	−0.438	82.20	98.10	99.70
37	34	680	1.54	0.109	90.80	92.07	99.60
38	66	504	1.12	−0.153	91.30	98.70	99.80
39	87	222	0.85	−0.030	99.30	97.10	99.74
40	34	439	1.3	−0.049	93.10	95.20	98.60
41	36	120	0.98	0.125	85.00	88.10	98.60
42	49	929	0.031	0.636	92.00	95.00	99.50
43	125	530	0.87	0.000	92.78	88.89	99.70
44	54	250	0.14	−0.182	95.70	94.00	99.40
45	40	998	0.91	0.019	93.90	94.00	99.90
46	30	221	0.086	0.277	95.00	90.90	99.90
47	42	170	1.2	−0.036	88.00	98.00	98.00
48	39	353	0.55	−0.084	95.48	92.35	97.91
49	43	138	0.06	−0.079	79.50	75.30	98.90
50	48	200	0.5	0.135	97.80	83.20	99.90
51	60	660	0.84	−0.076	96.10	98.70	96.30
52	35	778	0.52	0.063	95.00	92.35	98.00
53	36	617	0.46	0.125	93.10	95.10	98.60

Determination of the mean and standard deviation across all units for each variable is straightforward. The values are determined by the following formula:

$$Z_{ij} = \frac{(O_{ij} - \bar{O}_j)}{\hat{\sigma}_j}$$

After these Z-scores are determined, they need to be re-scaled from zero for each variable, so that the minimum Z-score for each variable is zero. It is important to have the minimum Z-scores for each variable as zero because the objective function of the DEA model is constructed with the requirement of minimum inputs and outputs having values of zero. This is done by adding the absolute value of the minimum Z-scores to each Z-score for every variable. After this, data are standardized and re-scaled from zero, they are ready for analysis (see, Table 2).

Analysis Results

Benchmarking can be used to identify the gap between current conditions or performance and the desired benchmark, and it can provide the information to guide the design of changes in operations. Benchmarking is a learning experience. Those who succeed at it learn a great deal, and the brightest benchmarking stars use what they learn to improve operations. By comparing the performance of one's own operations with reputable performance standards, operation managers may do two things. First, they can assess, in a general sense, the adequacy of their factory's performance by examining it in the context of an external factory. Second, they can confirm the reasonableness of their performance expectations by reviewing what other factories are able to achieve. The CCR model for input optimization with constant returns to scale evaluations was conducted using the Frontier Analyst (2000) and the results are shown in Table 2. Here, the input minimization was used that is given by the level of outputs that the units produce. Their use of inputs has been reduced while maintaining their current level of outputs. It can be seen from the analysis that Factories 2, 3, 6, 14, 17, 29, 35, 41, 42, 46 and 49 are efficient with scores of 1.00. The remaining 42 factories are inefficient with scores of less than 1.00. The last column in Table 2 shows the DEA-based benchmarks for inefficient factories. For example, Factory 5 can utilize Factories 35 and 46 as possible benchmarks for improvement. In the Frontier Analyst, the benchmarks are obtained by identifying the reference set of efficient units to which the unit has been most directly compared when calculating its efficiency rating. An efficiency study not only provides an efficiency score for each unit but also indicated how much and where an inefficient unit of an area needs to improve in order to be efficient. This information can enable targets to be set, which could help guide an inefficient unit to improve its performance. For the purposes of classification, an OEE score of 0.85 or higher was deemed 'world class level'. This cut-off value can be changed to a different value. The last column in Table 3 shows the following classification.

HE: High OEE and efficient (Factories 6, 14, 42 and 46).
HI: High OEE and inefficient (Factories 5, 7, 8, 9, 12, 13, 15, 20, 21, 23, 24, 28, 31, 32, 38, 39, 40, 44, 45, 48, 51, 52 and 53).
LE: Low OEE and efficient (Factories 2, 3, 17, 29, 35, 41 and 49).

Table 2. Scaled data for DEA analysis and summary of DEA results

Factory #	xl	x2	x3	yl	y2	y3	y4	efficiency(%)	Bench mark
1	1.28	0.44	0.67	0.82	0.00	4.39	4.76	84.11	3,14,46
2	2.56	0.25	1.66	7.72	4.32	1.15	2.00	100	NA
3	0.64	0.35	1.17	1.21	0.03	4.44	4.69	100	NA
4	0.70	2.29	2.46	0.82	4.05	0.00	4.75	41.01	35,46
5	0.70	1.73	2.11	0.72	4.32	4.63	4.07	55.9	35,46
6	0.35	3.66	0.72	0.69	3.27	4.63	2.48	100	NA
7	2.91	2.67	0.94	0.95	3.08	4.11	4.76	21.45	2,14,46
8	1.05	1.59	1.17	1.15	3.73	3.56	4.69	35.33	27,46
9	2.21	0.45	3.40	0.70	4.21	3.18	3.79	63.17	14,29,46
10	1.63	2.48	1.36	0.65	1.81	4.08	2.35	25.85	3,46
11	1.45	0.34	1.91	0.60	3.23	4.08	2.62	84.88	3,14,79,46
12	0.93	2.61	1.66	0.78	3.82	4.19	0.00	37.06	6,35,46
13	2.09	1.94	2.01	0.55	4.04	4.46	2.21	30.24	3,14,79,46
14	1.34	0.31	0.15	1.00	3.17	3.94	4.76	100	NA
15	0.93	3.66	1.91	1.07	3.79	3.89	4.71	33.22	6,35,46
16	0.52	3.24	2.91	0.55	3.66	3.55	3.03	38.94	35,46
17	0.17	1.27	2.68	0.89	3.44	3.43	4.41	100	NA
18	1.40	0.47	2.46	0.87	4.29	2.38	4.69	76.52	14,29,46
19	1.10	1.62	3.65	0.63	3.31	3.27	4.68	32.53	29,46
20	0.87	0.66	3.40	0.64	4.09	3.61	3.66	67.99	3,29,46
21	1.63	1.98	2.01	0.66	3.95	3.98	4.62	28.71	3,29,46
22	0.47	1.36	2.73	0.73	1.85	2.02	4.07	53.26	17,46
23	1.28	2.32	1.94	0.85	3.12	4.58	4.76	34.57	35,46
24	0.64	1.23	1.76	1.10	3.82	3.79	4.04	55.89	35,46
25	1.34	0.56	3.40	0.69	2.37	4.43	4.35	64.31	3,14,79,46
26	1.05	3.44	0.99	0.94	3.33	3.35	4.07	29.65	6,35,46
27	0.35	1.19	2.97	0.64	1.58	4.38	2.35	89.9	35,46
28	1.80	0.50	2.11	0.84	4.50	4.63	4.76	76.85	3,14,79,46
29	0.64	0.00	2.93	0.07	2.22	1.54	4.07	100	NA
30	0.70	1.74	1.77	1.52	3.29	2.28	4.31	62.05	2,35,46
31	0.99	0.90	1.81	1.23	2.40	4.63	4.76	58.9	3.29,46
32	0.99	1.12	3.90	0.43	3.21	4.42	2.48	52.01	3,46
33	3.20	2.57	3.15	0.63	3.05	3.80	3.66	18.14	3,14,79,46
34	1.05	0.46	1.34	0.57	2.34	4.61	4.69	89.19	14,29,46
35	0.00	1.74	2.26	0.48	3.05	3.92	3.24	100	NA
36	0.41	0.93	1.84	0.00	1.98	4.38	4.55	93.92	35,46
37	0.58	2.00	3.75	0.84	3.26	3.57	4.48	45.08	17,35,46
38	2.44	1.44	2.71	0.44	3.33	4.46	4.62	33.7	3,14,79,46
39	3.66	0.54	2.04	0.62	4.52	4.24	4.58	63.63	2,14.29
40	0.58	1.23	3.15	0.59	3.60	3.99	3.79	62.3	35,46
41	0.70	0.22	2.36	0.86	2.40	3.04	3.79	100	NA
42	1.45	2.79	0.00	1.64	3.44	3.96	4.41	100	NA
43	5.87	1.52	2.09	0.67	3.55	3.14	4.55	22.5	14,29,46
44	1.74	0.63	0.27	0.39	3.98	3.83	4.35	70.53	14,29,46
45	0.93	3.01	2.18	0.70	3.72	3.83	4.69	31.4	6,35,46
46	0.35	0.54	0.14	1.09	3.88	3.41	4.69	100	NA
47	1.05	0.38	2.91	0.61	2.84	4.36	3.38	88.75	3,14,79,46
48	0.87	0.96	1.29	0.54	3.95	3.61	3.32	53.39	3,14,79,46
49	1.10	0.27	0.07	0.55	1.58	1.32	4.00	100	NA
50	1.40	0.47	1.17	0.87	4.29	2.38	4.69	88.36	14,29,46
51	2.09	1.94	2.01	0.55	4.04	4.46	2.21	30.24	3,14,79,46
52	0.64	2.31	1.22	0.77	3.88	3.61	3.38	46.24	35,46
53	0.70	1.80	1.07	0.86	3.60	3.98	3.79	48.56	6,35

Table 3. Factory classification based on OEE and DEA efficiency

Factory #	OEE	Efficiency	Classification	Factory #	OEE	Efficiency	Classification
1	67.55	84.11	LI	28	99.20	76.85	HI
2	69.62	100	LE	29	63.80	100	LE
3	67.97	100	LE	30	74.56	62.05	LI
4	62.90	41.01	LI	31	85.00	58.9	HI
5	97.02	55.9	HI	32	86.11	52.01	HI
6	87.90	100	HE	33	82.52	18.14	LI
7	86.10	21.45	HI	34	84.35	89.19	LI
8	86.39	35.33	HI	35	82.80	100	LE
9	85.47	63.17	HI	36	80.40	93.92	LI
10	74.97	25.85	LI	37	83.27	45.08	LI
11	84.19	84.88	LI	38	89.93	33.7	HI
12	85.17	37.06	HI	39	96.17	63.63	HI
13	91.34	30.24	HI	40	87.39	62.3	HI
14	85.51	100	HE	41	73.84	100	LE
15	89.15	33.22	HI	42	86.96	100	HE
16	83.78	38.94	LI	43	82.22	22.5	LI
17	83.30	100	LE	44	89.42	70.53	HI
18	81.29	76.52	LI	45	88.18	31.4	HI
19	81.79	32.53	LI	46	86.27	100	HE
20	87.65	67.99	HI	47	84.52	88.75	LI
21	90.64	28.71	HI	48	86.33	53.39	HI
22	64.79	53.26	LI	49	59.21	100	LE
23	89.54	34.57	HI	50	81.29	88.36	LI
24	87.77	55.89	HI	51	91.34	30.24	HI
25	83.03	64.31	LI	52	85.98	46.24	HI
26	81.71	29.65	LI	53	87.30	48.56	HI
27	75.25	899	LI				

LI: Low OEE and inefficient (Factories 1, 4, 10, 11, 16, 18, 19, 22, 25, 26, 27, 30, 33, 34, 36, 37, 43, 47 and 50).

From the four classification of factories HE, LI, LE and HI, HE factories are the benchmarking performers and these are the type of factories with high OEE (>85%) and efficiency. HI consists of inefficient factories with high OEE (>85%) and these factories may have unrealized potential. LE consists of efficient with low OEE (<85%). Since LE factories are already efficient, DEA does not provide benchmarks for improvement. Finally LI reflects the problem factories. The factories in this cluster LI need to improve their performance. From the classification of factories, Factories 6, 14, 42 and 46 are considered to be excellent performers for benchmarking purposes. For example, Factory 5 with the OEE value of 97.02 and an efficiency score of 55.90% was chosen for special analysis and examination of the value for the input and output variables alongside those of the efficient factories. In comparison with the efficient Factory 35, the analysis identified that Factory 5 should reduce the input variable X_1 by 44%, X_2 by 44%, and X_3 by 70% and increase the output variables Y_1 by 83%, Y_2 by 14%, and Y_4 by 45% to become efficient, as illustrated in Figure 1. Without this efficiency analysis, Factor 5 may be satisfied by its high OEE performance and never find the opportunity for improving its efficiency.

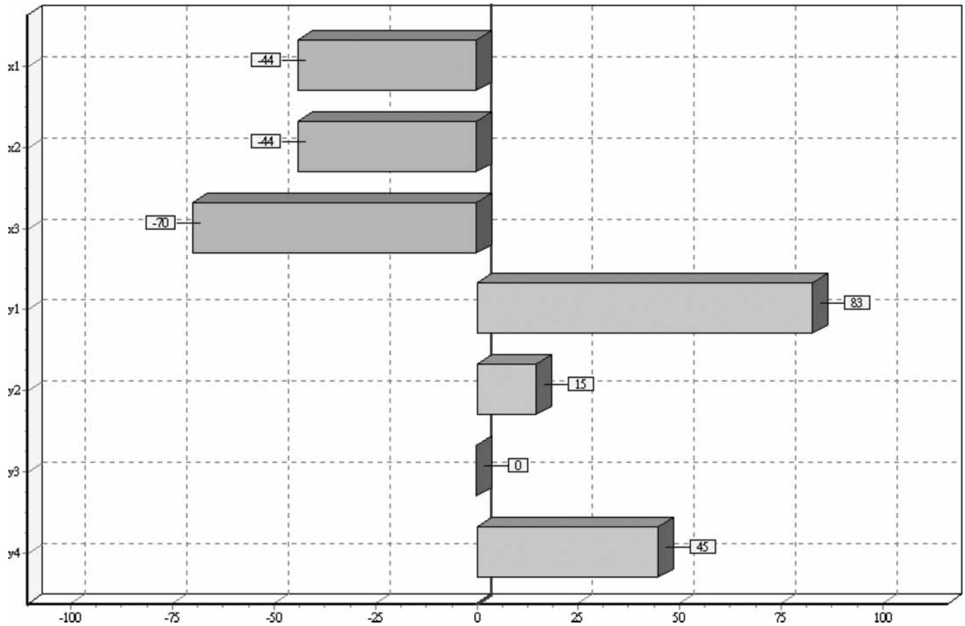

Figure 1. Potential improvement for Factory 5

Managerial Implication and Prediction Model

The study performed in this work has important managerial implications. The methodology proposed in this article can be utilized to evaluate the efficiency of implementing TPM for the benchmarking analysis. Benchmarking is usually the initial step that factories must undertake before being involved in business process re-engineering and improvement strategies. Multidimensional benchmarking assists factories in moving from where they are to where they should be. The proposed methodology can identify a peer group of efficient factories against which to benchmark them. The actual improvement process may involve identifying the operating practices and procedures of the benchmark factories and engaging in re-engineering programs.

Furthermore, multiple linear regression analysis is employed with an aim to obtain a prediction model between the efficiency score and the seven variables. The software Minitab (2000) was used for the multiple regression analysis and the prediction model is given as follows:

$$\begin{aligned}\hat{E} = {} & 233.2251 - 0.6466X_1 - 0.0537X_2 - 17.8389X_3 + 6.5680Y_1 - 0.3346Y_2 \\ & + 0.0448Y_3 - 0.7494Y_4\end{aligned}$$

where $X_1 =$ the months from the start of the TPM program to winning the TPM award, $X_2 =$ the number of employees, $X_3 =$ the TPM budget as a percentage of sales, $Y_1 =$ the sales growth from the beginning of TPM to obtaining the TPM award, $Y_2 =$ the availability of the equipment, $Y_3 =$ the performance efficiency of the equipment, and $Y_4 =$ the quality rate. The analysis of variance table is shown in Table 4. The residual analysis

Table 4. The analysis of variance

	df	SS	MS	F	P-value
Regression	7	25262.57	3608.94	11.39	3.29E-08
Residual	45	14257.17	316.83		
Total	52	39519.74			
	Coefficient	Std error	t-statistic	P-value	
Intercept	233.2251	194.2388	1.2007	0.236	
x1	−0.6466	0.1506	−4.293	9.25E-05	
x2	−0.0537	0.0084	−6.4015	7.9E-08	
x3	−17.839	6.3845	−2.7941	0.008	
y1	6.5680	4.3278	1.5176	0.136	
y2	−0.3346	0.3958	−0.8453	0.402	
y3	0.0448	0.3647	0.1227	0.903	
y4	−0.7494	1.8221	−0.4113	0.683	

shows that the assumptions of normality, homogeneity of variance–covariance matrices, linearity and multicollinearity are all satisfied for the above multiple linear regression model. We can use the above equation to obtain the estimated parameters, and then it can be easily used to predict the efficiency score for monitoring the efficiency of implementing TPM.

One issue about implementing TPM may be involved in many small size factories. With respect to the efficiency scores of 53 factories, we can test whether there is any difference between the large factories of and the small factories. Here, we define a firm with more than 500 employees is called large. Therefore, a factory of less then 500 employees is considered to be small. The summary statistics of the efficiency score from these two types of factories are shown as follows:

Parameter	Small size factories, $n_2 = 28$	Large size factories, $n_1 = 25$
$\hat{E}$	$\bar{x}_S = 79.92$ $s_S = 17.60$	$\bar{x}_L = 43.29$ $s_L = 23.66$

Since the p-value $= 2.1 \times 10^{-8}$, we cannot reject the alternative hypothesis $\mathrm{H}_1 : \mu_S > \mu_L$ at the 95% confidence level. That is, there is strong evidence indicating that the mean of estimated efficiency score from the small factories is greater than that of the large factories. Further, from the DEA results, 11 factories are efficient with scores of 1.00, with eight of them classified as small. The small size factories may have more relative efficiencies than large size factories.

Conclusions

This article has proposed a simple methodology for efficiency evaluation in TPM. The analysis is based on a CCR model with input minimization that allows for incorporation of multiple inputs and outputs in evaluating a single, composite score, referred to as efficiency. The efficiency scores in combination with the OEE scores are utilized in classifying factories of four categories. Benchmarks are provided for improving the operations of poorly performing factories. The efficiency scores resulting from the DEA for all the 53 units were obtained from the TPM awards in 1996–1999. Furthermore, a multiple linear regression model was constructed to estimate the efficiency score of implementing TPM. The company can use this multiple linear regression model to obtain the estimated efficiency score for monitoring the efficiency of implementing TPM. In addition, based on the hypothesis tested for the mean of an efficiency score, the small size factories (number of employees ≤ 500) may have more relative efficiencies than that of large size factories (number of employees >500).

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