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Measurement of Production Efficiency in Semiconductor Assembly House: Approach of Data Envelopment Analysis

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Abstract

Because semiconductor assembly plants generally apply individual indicators to monitor manufacturing processes, this research proposes the approach of data envelopment analysis (DEA) to evaluate production performance from the perspective of overall efficiency. Our DEA models are composed of 3 input variables (average employee number, average labor hours, and cost of goods sold) and 4 output items (production output, average overall equipment effectiveness, production cycle time, and production ratio). To test the practicability of proposed models, one semiconductor assembly company was selected to investigate the relative efficiency of its 10 manufacturing plants. DEA-based Malmquist productivity index was also applied to describe the productivity change over time. Findings show that the main cause of technology inefficiency for the sample company is its inappropriate resource allocation in the aspect of operation efficiency. From the viewpoint of efficiency variation, the productivity of six relatively efficient plants was increasing during 2 years of observations while the productivity of the other four plants was decreasing at the same period. Through the analysis of slack variable and sensitivity analysis, number of employees in the relatively inefficient manufacturing plants may cause additional hidden costs and wastes. Our analysis results not only demonstrate the applicability of DEA approach for the measurement of production efficiency in semiconductor assembly industry but also provide this industry with methodology to indentify where to improve operational performance.

Keywords: *Efficiency Assessment, Data Envelopment Analysis, Malmquist Analysis*

1. Introduction

As the semiconductor assembly industry is capital-intensive, operations management becomes one of the important issues for its business effectiveness. Especially under the pressure of limited profit margin and customer requirements, plants have to enhance their operating efficiency so as to improve the competitive advantage. Currently, the manufacturing process of semiconductor assembly plant faces bottlenecks of die bond, wire bond and potting sites. For instance, the outputs of most die bonding machines are contricted by their actuation modes of absorption and desorption. Moreover, wire bonding machine is constricted by the number and arc of wire bond, while potting machine is restrained by the time of potting. In terms of cost, although employees account for 15%-20% of total expenditure, machines of die bond, wire bond and potting sites are still the largest investments for the semiconductor assembly house. Accordingly, management tends to focus on enhancing man-machine ratio and simplifing SOP to reduce human cost and improve productivity. In addition, various performance indexes are also applied routinely to monitor operational efficiency and quality for further improvement. However, the performance indexes adopted by the semiconductor manufacturing factories usually consider single angle like machine breakdown or yield rate. Although this kind of method is easy to calculate and understand, index approach has limitations because it's unable to identify the causes of inefficiency and to reflect the actual relative efficiency among plants. Therefore, evaluation methods that can consider both the inputs and outputs of manufacturing plants could provide more reliable findings for management to adjust their production operations.

In order to bridge the gap between practical and theoretical issues in the semiconductor manufacturing industry, this paper considered Data Envelopment Analysis (DEA) method for performance assessment. This approach not only takes into account input-output variables but also proves to be useful for efficiency analysis. Without specifying the production functions in advance, we are also able to trace the sources of inefficiency for every evaluated plant. Together with DEA-based Malmquist productivity measurement, productivity rate of growth for each plant can be further analyzed to understand their progress or regression during a specific period. Hence, the main purposes of this study include the analysis of operational performance and changes for the semiconductor assembly house, and the improvement solutions for inefficient plants assessed. In the following discussion, we start with the brief review of past research regarding the efficiency assessment in the electronics industry. Then section 3 describes the DEA methodology used in this study. To validate the applicability of our proposed approach, one semiconductor assembly company was selected to investigate the relative efficiency of its 10 manufacturing plants. Findings of this case study are discussed in section 4. Finally, we conclude our research in the final section.

2. Efficiency Assessment of Electronics Industry

In the electronic manufacturing industry, common methods of efficiency assessment include machine utilization rate, regression analysis, and DEA. Leachman and Hodges (1996) used regression analysis to study 16 wafer factories, and obtained the production cycle and yield rate for each product line. Thore et al. (1996) applied DEA method to evaluate the cycle time efficiency of computer manufacturing industry in the U.S., so as to find out how to improve machine's production rate and to maintain efficiency. Shang and Sueyoshi (1995) analyzed the efficiency of flexible production systems, and found that DEA method could be applied to evaluate different manufacturing systems. Their study also compares the efficiency of different production lines and gives managers the suggestions for improvements. Beeg (2004) used crash time and average repair time to establish the capability indicators of machine and personnel. Besides, Beeg took into considerations the variables of production amount, overall equipment efficiency (OEE), and production ratio as the items of outputs for DEA models. Ertray and Ruan (2004) employed DEA method to evaluate workers' efficiency in mobile manufacturing plants. Work hours and staff allocation are listed as the efficiency assessment of inputs. Hosseinzadeh and Ghasemi (2007) investigated the efficiency and productivity in telecommunication companies through DEA models and Malmquist productivity index. Pan et al. (2008) explored the managerial and productive technical efficiencies of Taiwan's IC design industry. They also adopted DEA models and DEA-based Malmquist method to examine the performance of 72 companies from 2003 to 2005.

In the semiconductor industry, OEE is often employed to measure productivity (SEMI, 1999). Other common indicators include: availability efficiency, efficiency ratio, operating efficiency, and quality efficiency (Nakajima, 1988; Leachman, 1995; Konopka, 1996). Availability efficiency is defined by the difference between total production time and downtime over total production time. Meanwhile, efficiency ratio is the ratio of ideal cycle time to actual cycle time. Operating efficiency is the ratio of total production time to facility operating time. Accordingly, we can rank performance by the cross product of efficiency ratio and operating ratio. Additionally, quality efficiency is defined by the difference between total production volume and total returns over total production volume. Hence, each machine can use one of the above indicators to evaluate their respective performance. Integrated performance index can be also computed by the average performance of all machines. Furthermore, Thomas (2000) applied DEA approach to measure efficiency of semiconductor manufacturing operations. Input variables in DEA models include mean time between failures, scrap/1000 wafer moves, cycle time, and downtime. Meanwhile, wafer moves, OEE, activity ratio (actual moves/planned moves) are output variables. Liu and Wang (2007) also employed DEA models to assess the Malmquist productivity of semiconductor packaging and testing firms in Taiwan. Their Malmquist productivity considers 3 major measurements, which are technical change, frontier forward shift, and frontier backward shift of a company over two consecutive periods. From the above review of past studies, DEA has been proved to be a successful evaluation approach for efficiency performance in the semiconductor industry. Hence, this study would like to further investigate how to apply the DEA method to measure the production efficiency and efficiency change in the semiconductor assembly industry.

3. Methodology

3.1 Decision Making Unit (DMU)

Decision making unit is any entity that is to be assessed by its abilities to convert inputs into outputs (Charnes et al., 1978). According to Golany and Roll's (1989) definition, DMUs must be a group of homogeneous units, but there should be some differences between them.

Thus, this study took 10 independent factories (denote P*i*, *i* = 1,…,10) of a certain semiconductor assembly company in Taiwan as the target of assessment. Monthly data of activities were retrieved from the manufacturing execution system during the period of 2005/01-2006/12. These 10 factories generally had common manufacturing machines. For example, the same type of wire bonder machines can produce lead frame and BGA products. Factories could support each other and do cross feeding. P1, P2, P3, P4, P5 and P6 factories mainly manufactured consumptive IC products, the general logic and IC control lead-frame products, such as PDIP, PLCC, QFP, and TQFP; while P7, P8, P9 and P10 factories mainly manufactured graphics chip, CPU, LCD driver chip and other mid and high-end BGA products, such as BGA, TFBGA, QFN, and FBGA.

3.2 Inputs and Outputs

To select the input variables and output variables for the DEA models used in this study, factors that affect overall production processes, costs, operating time, product quality, and machine efficiency were under our considerations. Based on the results of past research and on-site investigation of engineers, three input variables were chosen and are summarized as follows:

(1) Average employee number: the average number of employees per month;
(2) Average labor hour: the average work hours per month;
(3) Average cost of goods sold: the average cost of goods sold divided by the net sales per month.

All of the input data were collected from the personnel database of target manufacturer for each plant.

Besides, the output variables of DEA models are defined as follows:

(1) Production output: the actual production of each factory per month;
(2) Average OEE: OEE = Availability Ratio x Performance Ratio x Quality Ratio, where availability ratio is the share of the actual production time and the planned production time, performance ratio is the loss of production due to under-utilization of the machinery, quality ratio is the amount of the production that has to be discharged or scrapped;
(3) Production cycle time: time it takes for production personnel to make the product available for shipment to the customer;
(4) Production ratio: the actual delivery of each factory per month divided by the planed delivery.

All of the output observations were collected from the manufacturing execution system of each plant.

3.3 Research Models

The basic DEA model of efficiency analysis is composed of the inputs and outputs of DMUs. This approach tends to reduce the multiple-output/multiple-input situation to a single 'virtual' output and 'virtual' input. The ratio of single output to single input for a particular DMU, which is a function of the multipliers, forms the objective function for optimization. Because DEA approach is empirically-oriented and has no a priori assumptions like other approaches, it has been applied to a number of studies involving efficient frontier estimation. To encounter different problem issues, there is a variety of alternate DEA models to evaluating performance. The CCR model with constant returns to scale (Charnes et al., 1978) and the BCC model with variable returns to scale (Banker et al., 1984) were applied in this study to evaluate efficiency performance among manufacturing plants of semiconductor assembly house. Suppose we have m different inputs and s outputs for n DMUs. The CCR model can be described by

$$\begin{aligned}
&Min\ h_k = \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)\\
&s.t.\\
&\sum_{j=1}^{n} \lambda_j X_{ij} - \theta X_{ik} + s_i^- = 0\\
&\sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ = Y_{rk}\\
&X_{ik} = \theta X_{ik} - s_i^-\\
&Y_{rk} = Y_{rk} + s_r^+\\
&\forall \lambda_j, s_i^-, s_r^+ \geq 0; j = 1,\ldots,n; i = 1,\ldots,m; r = 1,\ldots,s; \theta \in R
\end{aligned} \tag{1}$$

The mathematical meaning of Eq. (1) is to get the minimum value of h_k in restriction conditions, where Y_{rj} is r-th output for plant j, X_{ij} is i-th input for plant j, s_i^- is slack variable, and s_r^+ is surplus variable. The optimal solution of θ must be positive and yield an efficiency score for a specific DMU. The necessary and sufficient condition of every DMU with relative efficiency is $\theta = 1$ and $s_i^- = s_r^+ = 0$. However, CCR model is assumed to be the linear programming model with constant returns to scale, which is not necessarily in line with the actual situation of industry. Therefore, Banker et al. (1984) replaced with variable returns to scale, that is, $\Sigma\lambda = 1$ was added into the above formula and get the BCC model in Eq. (2):

$$\begin{aligned}
&Min\ h_k = \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)\\
&s.t.\\
&\sum_{j=1}^{n} \lambda_j X_{ij} - \theta X_{ik} + s_i^- = 0\\
&\sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ = Y_{rk}\\
&\sum_{j=1}^{n} \lambda_j = 1\\
&X_{ik} = \theta X_{ik} - s_i^-\\
&Y_{rk} = Y_{rk} + s_r^+\\
&\forall \lambda_j, s_i^-, s_r^+ \geq 0; j = 1,\ldots,n; i = 1,\ldots,m; r = 1,\ldots,s; \theta \in R
\end{aligned} \tag{2}$$

After solving the technical efficiency values based on CCR and BCC models specified in Eq. (1) and (2), scale efficiency (SE) is obtained, which is the ratio of two values. SE = 1 represents scale efficiency and SE < 1 represents scale inefficiency, where SE can be divided into increasing returns to scale (IRS) and decreasing returns to scale (DRS). $\Sigma\lambda = 1$ implies constant returns to scale, $\Sigma\lambda > 1$ indicates IRS, and $\Sigma\lambda < 1$ describes DRS.

In order to find out the real value of comparative efficiency in different periods, and solve the shortcomings of assessed unit, this study used Malmquist productivity analysis as the basis for measurement and comparison. This approach can show the changes in technical efficiency and technical change process with the definition of Malmquist index specified in Eq. (3):

$$M_0 = \left[\frac{\theta_0^t(x^{t+1}, y^{t+1})}{\theta_0^t(x^t, y^t)} \frac{\theta_0^{t+1}(x^{t+1}, y^{t+1})}{\theta_0^{t+1}(x^t, y^t)} \right]^{1/2} \quad (3)$$

where $\theta_0^t(x^{t+1}, y^{t+1})$ denotes the relative efficiency of a particular DMU in period t + 1 against the performance of those DMUs in period t. Productivity $M_0 > 1$ implies that the productivity is improved over time whereas the productivity is declined when $M_0 < 1$. This approach not only reveals patterns of productivity change but also identifies the strategy shifts of individual plant.

4. Results

4.1 Efficiency analysis

Table 1 and 2 summarize the efficiency scores evaluated by the CCR and BCC models respectively for each plant in year 2005 and 2006. The CCR model assumes constant returns to scale while the BCC model allows for variable returns to scale.

DMU	Efficiency	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
P1	CCR	0.815	1	0.692	0.682	0.682	0.701	0.701	0.701	0.701	0.701	0.700	0.700
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	0.815	1	0.692	0.682	0.682	0.701	0.701	0.701	0.701	0.701	0.700	0.700
P2	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P3	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P4	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P5	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P6	CCR	0.819	0.790	0.802	0.802	0.802	0.846	0.846	0.917	0.917	0.917	0.914	0.914
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	0.819	0.790	0.802	0.802	0.802	0.846	0.846	0.917	0.917	0.917	0.914	0.914
P7	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P8	CCR	0.745	0.629	0.612	0.612	0.612	0.612	0.610	0.612	0.648	0.648	0.691	0.741
	BCC	1	1	0.98	0.932	0.933	0.933	1	1	1	1	1	1
	SE	0.745	0.629	0.624	0.656	0.656	0.656	0.610	0.612	0.648	0.648	0.691	0.741
P9	CCR	0.860	0.831	0.829	0.818	0.818	0.812	0.806	0.806	0.829	0.829	0.824	0.827
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	0.860	0.831	0.829	0.818	0.818	0.812	0.806	0.806	0.829	0.829	0.824	0.827
P10	CCR	0.809	0.832	0.847	0.813	0.813	0.916	0.916	0.916	0.916	0.916	0.916	0.919
	BCC	1	0.907	1	1	1	1	1	1	1	1	1	1
	SE	0.809	0.916	0.847	0.813	0.813	0.916	0.916	0.916	0.916	0.916	0.916	0.919

Table 1. The efficiency scores of DMUs in 2005

DMU	Efficiency	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
P1	CCR	0.701	0.679	0.734	0.811	0.785	0.785	0.801	0.867	0.857	0.815	0.835	0.810
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	0.701	0.679	0.734	0.811	0.785	0.785	0.801	0.867	0.857	0.815	0.835	0.810
P2	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P3	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P4	CCR	1	1	1	0.986	1	1	1	1	1	1	1	1
	BCC	1	1	1	0.996	1	1	1	1	1	1	1	1
	SE	1	1	1	0.989	1	1	1	1	1	1	1	1
P5	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P6	CCR	0.916	0.828	0.828	0.828	0.828	0.828	0.862	0.863	0.843	0.863	0.833	0.859
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	0.916	0.828	0.828	0.828	0.828	0.828	0.862	0.863	0.843	0.863	0.833	0.859
P7	CCR	1	1	1	1	1	1	1	1	1	1	1	1
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	1	1	1	1	1	1	1	1	1	1	1	1
P8	CCR	0.714	0.628	0.627	0.605	0.605	0.599	0.637	0.612	0.640	0.640	0.657	0.647
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	0.714	0.628	0.627	0.605	0.605	0.599	0.637	0.612	0.640	0.640	0.657	0.647
P9	CCR	0.808	0.766	0.752	0.752	0.752	0.753	0.752	0.762	0.766	0.681	0.681	0.708
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	0.808	0.766	0.752	0.752	0.752	0.753	0.752	0.762	0.766	0.681	0.681	0.708
P10	CCR	0.916	0.922	0.921	0.921	0.888	0.889	0.874	0.864	0.874	0.826	0.846	0.840
	BCC	1	1	1	1	1	1	1	1	1	1	1	1
	SE	0.916	0.922	0.921	0.921	0.888	0.889	0.874	0.864	0.874	0.826	0.846	0.840

Table 2. The efficiency scores of DMUs in 2006

If taking the time interval of month for analysis, plants P2, P3, P4, P5 and P7 are efficient in CCR Model during the observation period. On the other hand, plants P1, P6, P8, P9, and P10 are inefficient for all 24 months. In terms of factory analysis, plant P_1 has only one month achieving technical efficiency, and the rest are scale inefficiency. Besides, plants P2, P3, P4, P5 and P7 all have scale efficiency. But plants P6, P8, P9 and P10 are scale inefficiency.

From the SE analysis, the study found that plants P2, P3, P5 and P7 maintained efficient during the observation period, whereas plants P6, P8, P9 and P10 had no scale efficiency for 24 months. But the SE inefficiency factories all had efficiency value of 1 in the BCC model. This phenomenon implies that their inefficiency is possibly from the influence of scale inefficiency. Additionally, the efficiency scale of plant P1 is 1 in only one month while its performance remains inefficient for the remaining 23 months. This finding also indicates the possibility of scale inefficiency. Therefore, reducing the scale of production can improve scale inefficiency.

Moreover, although plant P4 had technical and scale inefficiency only in April 2006, it had the overall relative efficiency of 1 for the rest of observations. The main reason is the input imbalance between average employee number and average labor hours. After adjusting the related imbalanced variables, the overall relative efficiency was recovered to 1. Meanwhile, plant P8 has similar situation like plant P4. It had technical and scale inefficiency from March to July in 2005 and the rest had the overall relative efficiency of 1. After adjusting related variables, the overall relative efficiency can be recovered to 1. Similar implication can be inferred for plant P10. Therefore, although each factory couldn't use input resource effectively to achieve the output with scale efficiency in a short time, it can still achieve efficiency if related variables were adjusted. This information provides an important managerial impact on resource control of manufacturing plants.

4.2 Analysis of Slacks and Returns to Scale

We further performed the analysis of slack variables to understand the improvements of inefficient DMUs on inputs. Meanwhile, returns to scale analysis was applied to identify whether a proportional change in inputs result in the same proportional change in outputs. IRS indicates that proportional changes in inputs result in a more than proportional changes in outputs. On the other hand, DRS implies the opposite changes in outputs. Therefore, after analysis of slacks and returns to scale, this study summarizes the influential elements of the efficiency in each inefficient factory as follows:

(1) P1 is DRS, which should be improved through reducing its input of resources, especially the control of employee number and labor hours.
(2) P6 is DRS, which should be improved through reducing its input of resources, especially the control of employee number.
(3) P8 is DRS, which should be improved through reducing its input of resources, especially the control of employee number and labor hour.
(4) P9 is DRS, which should be improved through reducing its input of resources, especially the control of labor hour.
(5) P10 is DRS, which should be improved through reducing its input of resources, especially the control of employee number and average cost of goods sold.

4.3 Sensitivity Analysis

The sensitivity analysis is mainly to get CCR overall efficiency of each assessed factory through respectively removing inputs and outputs. The resulted value is compared with the original input-output efficiency. Sensibility analysis can be used to understand the impact of each variable on efficiency and to find out the sources of efficiency and inefficiency for each unit assessed. After sensitive analysis, the findings of this study are as follows:

(1) When deleting "average employee number": P8's efficiency is significantly reduced by about 10%, so average employee number is the advantage to enhance the overall efficiency. P4's efficiency decreases significantly only in 6 months. Its efficiency scores are among 0.98-0.99, which results in decreased overall efficiency.
(2) When deleting "average labor hour": The efficiency scores of P6, P8, and P10 are reduced by 1%, 1% and 5% respectively. Because plant P4's efficiency decreases significantly only in 3 months, it can explore whether the labor hour is excessive in the period.
(3) When deleting "average cost of goods sold": P2's efficiency values are reduced by about 15%. Meanwhile, P4's efficiency decreases to 0.98 significantly only in one

month, and the rest months are not affected. Similarly, P5's efficiency decreases significantly only in 6 months. Thus, the average cost of goods sold has a significant impact on efficiency score.

(4) When deleting "production output": P2's efficiency values are reduced by about 50%, P6 was about 30%, P7 was about 77%, P8 was about 10%, P9 was about 30 %, and P10 was about 40%. Moreover, P3's efficiency decreases significantly only in 9 months, which are among 0.93-0.97. Hence, the production output also has a significant impact on efficiency score.

(5) When deleting "average OEE": P4's efficiency decreases significantly in 2 months, which are among 0.98-0.99. Its efficiency scores are not affected for the rest of months. So the average OEE is the advantage to enhance the overall efficiency.

(6) When deleting "production cycle time": P4's efficiency decreases to 0.98 significantly in one month, and the rest are not affected. So the production cycle time is the advantage to enhance the overall efficiency.

(7) When deleting "production ratio": P4's efficiency decreases to 0.99 significantly in 2 months, and the rest are not affected. So the production ratio is the advantage to enhance the overall efficiency.

Therefore when deleting average employee number, labor hour and production output, more than half of factories are affected (P2, P6, P7, P8, P9 and P10) and their efficiency scores decrease. Accordingly, these three variables are advantages enhancing the overall efficiency.

4.4 Malmquist Analysis

Finally, Malmquist productivity measure was used by this study to compare the efficiency value of each factory at different times. Table 3 shows the result of total factor productivity change (TFPC), technical efficiency change (TEC), and technical change (TC) in assembly factories.

Factory	TFPC, TEC, TC
P1	TFPC ⇈ , TEC ⇈ , TC ⇈
P2	TFPC ⇈ , TEC ⇈ , TC ⇈
P3	TFPC ⇈ , TEC ⇈ , TC ⇈
P4	TFPC ⇈ , TEC ⇈ , TC ⇈
P5	TFPC ⇈ , TEC ⇈ , TC ⇈
P6	TFPC ⇊ , TEC ⇊ , TC ⇊
P7	TFPC ⇈ , TEC ⇈ , TC ⇈
P8	TFPC ⇊ , TEC ⇈ , TC ⇊
P9	TFPC ⇊ , TEC ⇊ , TC ⇊
P10	TFPC ⇊ , TEC ⇊ , TC ⇈

Table 3. The Malmquist Productivity Measure results of each assembly factory
Note: ↑ represents progress; ↓ represents backward

According to the results of Table 3, plants P1, P2, P3, P4, P5, and P7 have TFPC sustained progress, showing an improvement in productivity. On the other hand, plants P6, P8, P9 and P10 show a backward trend, which means the recession in productivity. Moreover, plants P1, P2, P3, P4, P5, P7 and P8 have enhancing changes in technical efficiency, showing an improvement in technical efficiency. But plants P6, P9 and P10 have recession in technical efficiency with no improvement in TEC. Besides, plants P1, P2, P3, P4, P5, P7 and P10 have enhancing technical changes, showing an improvement in production technology. However, plants P6, P8, P9 and P10 have recession in production technology with no improvement in TC.

4.5 Summary

This study conducted efficiency analysis, returns to scale analysis, analysis of slacks variable, sensitivity analysis and Malmquist productivity index analysis to assess the efficiency of 10 semiconductor assembly factories. The results are summarized as follows:

(1) Efficiency analysis: Plants P2, P3, P4, P5, and P7 have efficiency in 24 months. But plants P1, P6, P8, P9, and P10 have scale inefficiency in 24 months. Besides, plants P8 and P10 have a total of five months with technical and scale inefficiency.

(2) Analysis of slacks variable and returns to scale: plants P2, P3, P4, P5 and P7 have achieved returns to scale while plants P1, P6, P8, P9 and P10 are DRS.

(3) Sensitivity analysis: when deleting "production output", plants P2, P6, P7, P8, P9 and P10 have significantly decreased efficiency scores.

(4) Malmquist productivity index analysis: plants P1, P2, P3, P4, P5, and P7 have continued progress in TFPC, showing an improvement in productivity. But plants P6, P8, P9 and P10 have backward trend, which means the productivity has recession.

5. Conclusions

According to our empirical test in a semiconductor assembly house, this study found that the applications of DEA method could improve the shortcomings of single performance measurements with the considerations of influential inputs and outputs during the manufacturing processes. DEA approach also proves to provide constructive suggestions to enhance resource allocation. For example in our case company, the managers can reduce the corresponding resource if the employee number or labor hour is found over-allocated from DEA results. Together with the Malmquist productivity measure, engineers are able to assess the patterns of productivity change after strategy shifts. This also helps management to evaluate whether or not such shifts are making progress. As for future studies, the same research methods and input elements could be used to assess the efficiency among different semiconductor assembly plants for the other company. Robustness of DEA approach for semiconductor assembly house can be verified then. More important factors may be included in DEA models to enhance its practicability for semiconductor assembly house. Models other than CCR and BCC can be explored to extend the explanation power of DEA approach.

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