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A DEA window analysis on the product family mix selection for a semiconductor fabricator

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Abstract

In a competitive market, semiconductor fabricator must face an environment with multi-product types, multi-priority orders and demand changes in time. Since semiconductor fabrication has a very complicated production process, the above-stated characteristics make the production planning even more difficult. This paper applies data envelopment analysis (DEA) to find a set of product family mix that is efficient for the company to produce. To ensure long-term effectiveness in productivity and in profit gaining, window analysis is adopted to seek the most recommended set of product family mixes for manufacturing by measuring the performance changes over time. With this method, the performance of a mix in one period is compared not only with the performance of other mixes but also with its own performance in other periods. The proposed mechanism can provide guidance to the fabricator regarding strategies for aggregate planning so as to improve manufacturing efficiency.

Keywords: Data envelopment analysis; DEA; Product family mix; Window analysis

1. Introduction

Today's semiconductor market is not as prosperous as it was before, and the market has changed from producer-oriented to customer-oriented. A single optimization goal, such as throughput maximization or profit maximization that was usually pursued by companies, is not enough today to meet the production performance demanded by customers. Performances such as on-time delivery and production cycle time are highly emphasized by customers. Therefore, companies need to consider both customer satisfaction in demand and the ultimate profit goal of companies.

As the economy fluctuates and product (or process) develops, customer demands in product type and quantity change as a result. This also makes the demand of product family mix, where the products with similar processes are belonging to the same product family, changes over time. Bottleneck utilization rate thus fluctuates, and this further has an impact on performance indicators such as production cycle time, delivery rate and work in process (WIP). The production performance evaluation in this kind of variant environment is much more important and difficult than the one in an environment with stable product types and quantities.

Previous researches usually focused on product mix determination; instead, this paper will select the most appropriate product family mix due to two primary reasons. First, the demand forecast of each product type is very difficult; on the other hand, the demand forecast of each product family, which consists of similar products, is relatively easier and more efficient for performance evaluation. The second reason is that products belonging to the same product family have similar manufacturing processes, have certain degree of substitutability and require similar critical workstations such as bottleneck and capacity constrained resource (CCR). On the other hand, different

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product families require a more differentiated capacity demand. Therefore, the input and output indicators of different product family mixes have a greater difference than the ones of different product mixes. As a result, the evaluation of alternatives on product family mixes will be more outstanding.

Product family mix determination is one of the core problems in current semiconductor production planning system. In wafer manufacturing, production processes such as photolithography, developing and etching have a unique characteristic of re-entry. The number of re-entry of a distinct machine for each product family is different; therefore, there often is a situation that different product families are required to be processed on the same machine at the same time. The situation can happen too even in the same product families for processing the re-entry operations. Because of the above-mentioned process characteristic, a CCR may be overly utilized when customer orders are concentrated on a specific type of products, and this may lead to bottleneck wondering, decrease in throughput, elongation in production cycle time and decrease in delivery rate. Product family mix not only has an impact on production performance, it also has an effect on a firm's profit. This is because different product families have different process designs and recipes, and thus, prices. With different product family mixes, profit obtained by the firm is different.

In solving the long-term product family mix problem, we should not only optimize one single performance factor, but rather we need to make sure that the performances on a number of indicators are satisfactory in order to maintain the competitive advantage of the fab. To consider numerous aspects of performance, in recent years, researches have been done to solve the product mix problem by adopting multiple criteria decision-making concept and related tools. However, scholars only focused on the determination of product mix in a single period and did not consider the performance problem in a long-term demand-varying environment. In an environment with customer needs in unstable product mix and big demand fluctuation, the product family mix solved in a high demand time period may not be favorable in a low demand time period. Therefore, it is necessary to know how to set product family mix in a long term.

In this paper, multiple input and output indicators, such as total throughput, delivery rate, production cycle time, of the production system are included. In addition, the demand variation among several production periods are considered to find one or several product family mix alternatives that are most suitable for production. Using multiple performance indicators to evaluate system performance, previous methods usually required decision makers to give the importance weighting to each indicator, and the difference in weights given by different decision makers might make the performance evaluation results different. To prevent the weights from being influenced by the subjectivity of decision makers, data envelopment analysis (DEA), a methodology that does not require pre-assignment of weights, is adopted here to evaluate product family mix. However, DEA alone cannot solve the problem of long-term product family mix performance evaluation. Therefore, window analysis that can compare the relative efficiency of product family mixes in different time periods is also applied in this paper. With the consideration of long-term demand fluctuation, one or a few product family mix alternatives that have long-term competitive advantage can be determined, and the firm can follow the recommendation in accepting orders to be competitive in the demand-varying environment.

The rest of this paper is organized as follows. Section 2 begins with a brief review of the product mix and priority level problem in semiconductor manufacturing. Section 3 briefly reviews DEA methodology and window analysis. Section 4 presents the product family mix evaluation model. Some conclusions are made in Section 5.

2. Product mix problem

Wafer fabs require a very high capital investment in plant and equipment, from $US 500 million to 1 billion each, and involve the most complex manufacturing system among all the manufacturing industries. Wafer fabrication has an important property, wafer process reentry, which refers to multiple visits by a wafer lot to the same processing center at different times. With 300–500 processing steps in a wafer process and a flow time of usually more than twenty days, the fabrication process is of high complexity. Product mix also has a very big impact to the production performance. Production performance in a wafer fab is a result of the interaction among product mix, equipment, inventory, process technology and scheduling practices. These factors change continuously if, for example, an unexpected equipment down time or a change in product mix happens frequently. The interaction between various complex factors makes production planning a very challenging task.

In order to be competitive and to satisfy customers' demand of accelerating the speed of products entering into the market, a wafer fab often have multiple priority levels of orders, and higher priority must be given to some urgent lots. The production priorities can be divided into three categories: hot, rush and normal. A higher priority order can use a machine whenever there is no other higher priority or equal priority order in presence, but a lower priority order has to wait till the machine becomes available. Because of a longer waiting time, lower priority orders result in a longer production cycle time. When there are too many lots with higher priority, the variation in shop floor performance will increase and the system throughput will reduce (Atherton & Atherton, 1995; Ehteshami, Petrakian, & Shabe, 1992; Fronckowiak, Peikert, & Nishinohara, 1996; Narahari & Khan, 1997). A higher priority order can result in the loss of machine capacity if a full loading policy is not required for batch machines and thus, machines are not fully utilized. Bottleneck shifting can occur in consequence, and again have impact on the production of lower priority orders. Narahari and Khan (1997) developed an analytical method based on mean value analysis (MVA) to predict the performance of semiconductor manufacturing system in the presence of hot lots. The results also show that hot lots have a significant effect on the mean cycle time, variance of cycle time and throughput rate of normal lots. Because the changes in the ratios of different priority orders have a great impact on the system performance, fabs usually set a maximum limit on higher priority orders or fix the ratios for different priority orders in advance. Chung, Pearn, and Lee (2006) presented a preliminary application DEA to find a set of product mix efficient for the semiconductor manufacturing company to achieve the optimal production. Kang and Lee (2007) constructed a fuzzy analytic hierarchy process (FAHP) method with entropy weight to generate performance ranking of different priority mixes in semiconductor manufacturing.

In summary, product family mix has a tremendous impact to the production system even when the priority mix is fixed, and many performance measures such as cycle time, WIP level, throughput, bottleneck utilization rate will be affected. Organizing the available data is a complicated task; however, DEA can provide a good method to deal with multiple inputs and outputs and to evaluate which product family mix can provide a more stabilized production environment and a better overall outcome for a wafer fab.

3. DEA methodology and window analysis

This paper proposed a data envelopment analysis (DEA) approach to solve the product family mix problem. The theory, development and applications of DEA, as well as its strengths and weaknesses, have been discussed in many papers, and therefore, only a brief review is presented here (Charnes, Cooper, Lewin, & Seiford, 1994a; Cooper, Seiford, & Tone, 2000). In 1957, Farrell first proposed production frontier to measure production efficiency based on the concept of Pareto optimality, and a frontier function called the efficient production function is used to fit the points as a piecewise linear function (Farrell, 1957). The frontier is a reference for comparing the efficiency of various points, and production efficiency is separated into two types: technical efficiency and allocative efficiency. However, the study was limited to single input and output.

Charnes, Cooper, and Rhodes (1978) extended Farrell's idea of linking the estimation of technical efficiency and production frontiers and developed DEA to generate comprehensive performance measurement index. DEA is applied to measure efficiencies of decision-making units (DMU), whose efficiencies can be obtained through the evaluation of multiple inputs and outputs without the pre-assignment of the criteria weights. The position of a DMU relative to the efficient frontier, the envelopment constituted by all the DMUs, is measured as efficiency (Charnes et al., 1994a). From the output perspective, if the amount of an output can be increased for a DMU while the amount of any output does not decrease and the amount of all its inputs does not increase, then the DMU is inefficient. From the input perspective, if the amount of an input can be reduced while the amount of any other input does not increase and the amount of all its outputs does not decrease, then the DMU is inefficient. A DMU is found to be efficient if it lies on the efficient frontier, where there is no inefficiency in the utilization of inputs and outputs (Charnes et al., 1994a).

DEA was first applied to investigate not-for-profit organizations; however, in the past few years, more and more researches have extended the DEA methodology to an application in various sectors and domains to solve multicriteria optimization problems (Cooper et al., 2000). Since its first introduction, an enormous number of DEA evolved models have been constructed to meet the different conditions of the problems for the past two decades, and DEA has been proved to be a promising technique for evaluating performance (Charnes et al., 1994a; Cooper et al., 2000).

CCR model, the model we are adopting in this paper, is introduced by Charnes et al. (1978) to generate efficiency in ratio form, by obtaining directly from the data without requiring a *priori* specification of weights nor assuming functional forms of relations between inputs and outputs. An inefficient DMU can be made efficient by projection onto a point on the efficient frontier. The particular point of projection selected depends upon the orientation employed. In an output orientation (output maximization), maximal movement via proportional augmentation of outputs is stressed. In other words, given the level of inputs used, what level of outputs can be best achieved. On the other hand, an input orientation (input minimization), maximal movement toward the frontier through proportional reduction of inputs is focused. That is, given the level of outputs produced, how much inputs can be reduced while maintaining their current level of outputs.

Below is a brief introduction of the input-oriented DEA model developed by Charnes, Cooper and Rhodes, CCR_d-I (Charnes et al., 1978). Assume that there are n DMUs, and each is represented by DMU_j where $j = 1, \ldots k \ldots, n$. For each DMU, there are m inputs (X_{ij}; $i = 1, \ldots, m$) and r outputs (Y_{rj}; $r = 1, \ldots, s$). The input of factor i for DMU j is X_{ij}, and the output of factor i for DMU j is Y_{rj}. The efficiency of DMU_k can be obtained as follows:

$$\text{Min} \quad h_k = \theta_k - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{1}$$

$$\begin{aligned} \text{s.t} \quad & \sum_{j=1}^{n} \lambda_j X_{ij} - \theta_k X_{ik} + s_i^- = 0, \quad i = 1, \ldots, m \\ & \sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ = Y_{rk}, \quad r = 1, \ldots, s \\ & \lambda_j, s_i^-, s_r^+ \geqslant 0, \quad j = 1, \ldots, n, \quad i = 1, \ldots, m, \quad r = 1, \ldots, s \end{aligned} \tag{2}$$

where s_i^-, s_r^+ are the slack variables of inputs and outputs, respectively, λ_j is the weight for DMU_j, and θ_k is the relatively efficiency indicator of the kth DMU.

A very small positive value ε, which is called a non-Archimedean small number, represents that all s_i^{-*} and s_r^{+*} must be considered, and it is usually set to 10^{-4} or 10^{-6} in real application. When a DMU_k^* is relatively efficient, its θ_{k^*} is one, and its $s_i^{-*} = s_r^{+*} = 0$. This implies that the DMU is on the efficient frontier. If a DMU is relatively inefficient, its inputs and outputs deviated from the optimal solution can be expressed as $X_{ik^*} = \theta_{k^*} X_{ik} - S_i^{-*}$ and $Y_{rk^*} = Y_{rk} + S_r^{+*}$, respectively, where X_{ik} and Y_{rk} are the inefficient input and output; X_{ik^*} and Y_{rk^*} are the input and output for the DMU being efficient; and S_i^{-*} and S_r^{+*} represent the required reduction and addition of input and output.

In the original DEA analysis, each DMU is observed only once, that is, each example is a cross-sectional analysis of data (Charnes et al., 1994a). In many actual studies, observations for DMUs are frequently available over multiple time periods, and it is often important to perform a panel data analysis to focus on changes in efficiency over time. In such a circumstance, DEA window analysis can be adopted to detect trend of a DMU over time (Asmild, Paradi, Aggarwall, & Schaffnit, 2004; Charnes, Cooper, & Seiford, 1994b; Yue, 1992). The underlying assumption of window analysis, proposed by Charnes, Clark, Cooper, and Golany (1985), is that of a moving-average analysis and that each DMU's efficiency is represented in the window several times, instead of being represented by a single summary score (Charnes et al., 1985; Charnes et al., 1994a, 1994b; Yue, 1992). Each DMU in a different period is treated as a different DMU, and the performance of a DMU in a period can be contrasted with its own performance in other periods as well as to the performance of other DMUs (Asmild et al., 2004). In doing so, the number of data points in the analysis is increased, and this can be usable when small sample sizes are under consideration.

The use of window analysis offers an opportunity to know how performance evolves through a sequence of overlapping windows. A brief window analysis review is presented here (Sun, 1988). Assume there are N alternatives, $l = 1, \ldots, N$, and each alternative has data for period 1 to M, that is, $m = 1, \ldots, M$. The window length is fixed to be K, and the data from period $1, 2, \ldots, K$ will form the first window row, and the data from period $2, 3, \ldots, K, K+1$ will form the second row, and so on. With the addition of one window, one more period on the right will need to be shifted to, and a total of $M-K+1$ window rows are existed. Each window is represented by $i = 1, \ldots, M-K+1$, and the ith window will consist of the data in periods $j = i, \ldots, i+K-1$. In the same window, there are K sets of data to be evaluated; therefore, there are a total of $N \times K$ DMUs in that window.

DEA and window analysis have been adopted in many researches. For example, Mahadevan (2002) adopted them to explain the productivity growth performance of Malaysia's manufacturing sector using a panel data of 28 industries for 15 years. Asmild et al. (2004) combined DEA window analysis with the Malmquist index approach in a study of the Canadian banking industry for 20 years. In order to evaluate the performance of product/family mixes over time, DEA window analysis will be used in this paper. Charnes et al. (1994a) found that $K = 3$ or 4 tended to yield the best balance of informativeness and stability of the efficiency scores, and the $K = 4$ quarter window facilitated yearly planning and helped detect seasonal effects.

To apply window analysis, DEA is used first to evaluate the performance of all DMUs in the same window, and the efficiency, $E_{i,j}^l$, of each DMU will be entered in the right window position in the table. The procedure will be repeated $M-K+1$ times to obtain all the efficiency values in all windows. Then, window analysis used all the efficiency values of an alternative to generate some statistics following Sueyoshi (1992) approaches. The average efficiency (M_l) of alternative l is obtained by:

$$M_l = \frac{\sum_{i=1}^{M-K+1} \sum_{j=i}^{i+K-1} E_{i,j^l}}{K \times (M-K+1)}, \quad l = 1 \ldots N \tag{3}$$

The variance among efficiencies of alternative l, V_l, is calculated by:

$$V_l = \frac{\sum_i^{M-K+1} \sum_j^{i+K-1} (E_{i,j}^l - M_l)^2}{K \times (M-K+1) - 1}, \quad l = 1 \ldots N \tag{4}$$

The variance of efficiency reflects the fluctuation of efficiency values for each alternative. If an alternative has higher average efficiency and small variance, its ranking can be higher compared to other alternatives.

Column range, $CR_{l,m}$, can be used to compare the fluctuations of efficiencies among the alternatives. In each alternative, because the data of the first period ($m = 1$) and last period ($m = M$) are being analyzed in only the first and the $M-K+1$ window, respectively and thus, only one efficiency value is obtained for each of the two windows, the efficiencies in the first and last periods will not be included in the calculation of CR values. For other periods, the data of each alternative is used at least twice and at least two efficiency values are available for calculating CR values. $CR_{l,m}$ is the difference between the largest and the smallest efficiencies for alternative l in period m. That is,

$$\begin{aligned} &\mathrm{CR}_{l,m} = \mathrm{Max}(E_{i,m}^l) - \mathrm{Min}(E_{i,m}^l), \\ &\text{for } i = \max(m-K+1, 1), \ \ldots, \ \min(m, M-K+1) \\ &m = 1 \ \ldots \ M \end{aligned} \tag{5}$$

$\mathrm{CR}_{l,m}$ can be used to evaluate the stability of efficiency of an alternative in each period. Then, CR_l is the overall column range for alternative l, and it shows the greatest variation in efficiency of an alternative over different periods:

$$\mathrm{CR}_l = \mathrm{Max}_{m=2, \ldots, M-1}(\mathrm{CR}_{l,m}) \tag{6}$$

In addition, to understand the stability of an alternative over different periods, total range can be used. Total range is the difference between the maximum and minimum efficiency values of an alternative in all windows. The total range for alternative l is:

$$TR_l = \mathrm{Max}(E^l_{i,j}) - \mathrm{Min}(E^l_{i,j}), \quad \text{for} \quad i = 1, \ldots, M-K+1, \quad j = i, \ldots, i+K-1 \tag{7}$$

For $\mathrm{CR}_{l,m}$, CR_l, TR_l, the smaller the value, the more stabilized are the efficiency values for adopting alternative. With six evaluation periods and a window length of three periods, the efficiency values and relevant evaluations are as shown in Table 1.

4. Product family mix evaluation model

4.1. The selection of DEA model

To evaluate the long-term performance of product family mix in a wafer fab, we adopt the DEA window analysis in this paper for two reasons. One, window analysis can effectively analyze the relative performance of product family mixes in multiple periods and the variation of performances among the periods. Two, more input and output factors can be included in window analysis. In DEA, if the total number of input and output factors are greater than half of the number of DMUs, the correlation between the values of the original performance factors and the values obtained through the DEA models becomes smaller, and this makes the discriminating power decrease (Golany & Roll, 1989). However, window analysis treats the performance values of the same alternative in different periods as different DMUs. The number of DMUs, as a result, increases, and this can remedy the defect of the mathematical model in DEA.

In window analysis, the DMUs in each window need a DEA mathematical model to calculate the efficient values, and the selection of a DEA model that is suitable for the environment stated in this paper is very important. As stated in Section 3, CCR-I is applied to compare the input efficiency of product family mixes based on the same level of output.

4.2. The selection of input and output factors

The selection of factors is essential. Factors should be selected properly to represent other correlated factors so as to reduce number of inputs and outputs for the DEA model. For evaluating the product family mix in a semiconductor fab, data corresponding to these factors must meet the isotonicity required by DEA in order to obtain acute evaluation results. Isotonicity means that when an input increases, an output should not decrease, and vice versa (Golany & Roll, 1989). If one factor has a negative or very weak correlation with other inputs or outputs, in order to satisfy isotonicity, the factor needs to be deleted from the model. On the other hand, when two factors are perfectly positive correlated, that is, the correlation coefficient is one, the changes of one factor can be reflected by the changes of the other factor completely. In this case, only one factor is needed to evaluate the system performance.

Based on the above requirements, the most suitable input and output factors can be selected by the following steps:

Step 1: Have an interview with the relevant personnel and managers in the industry and obtain input and output factors that are considered to be most important. These factors are the candidate factors.
Step 2: Construct a virtual wafer fab by building a simulation model. Run this model under different scenarios so as to collect the data of the candidate factors.
Step 3: Calculate the correlation coefficients among the candidate factors. If there is any factor that has a negative correlation with other factors, delete the factor.
Step 4: If there are any two or more factors that are perfectly positive correlated, select the factor that has higher correlations with the rest of the factors.

4.3. Input and output candidate factors

Financial performance is always the highest concern of the top management. Production performance, on the other hand, is impacted by product family mix. Therefore, these two aspects of performance should both be considered in the evaluation of product family mix selection. After an interview with the related personnel of several semiconductor fabricators in Science-based Industrial Park in Taiwan, some candidate factors for wafer fab

Table 1
Window analysis of alternative l

Alternative	Period window	1	2	3	4	5	6	Mean efficiency	Variance	Total range
l	W_1	$E^l_{1,1}$	$E^l_{1,2}$	$E^l_{1,3}$				M_l	V_l	TR_l
	W_2		$E^l_{2,2}$	$E^l_{2,3}$	$E^l_{2,4}$					
	W_3			$E^l_{3,3}$	$E^l_{3,4}$	$E^l_{3,5}$				
	W_4				$E^l_{4,4}$	$E^l_{4,5}$	$E^l_{4,6}$			
	$CR_{l,m}$	X	$\mathrm{CR}_{l,2}$	$\mathrm{CR}_{l,3}$	$\mathrm{CR}_{l,4}$	$\mathrm{CR}_{l,5}$	X	CR_l		

X: omitted.

efficiency evaluation are selected. Below are the definitions of these factors:

1. *WIP in front of photolithography workstation* The circuit pattern of a wafer is constructed during photolithography. In order to achieve the pre-determined functions of final products, wafer batches must repeat photolithography activities, and thus, the re-entry characteristic is resulted. As WIP in front of the workstation increases, the smoothness of the wafer batch flow will be impacted. Therefore, this factor is an input that we would like to minimize from the view point of production control.
2. *Bottleneck utilization rate* The average utilization rate of the bottleneck in the system for a period of time. Because the number of layers and processing time are different for different product families, an inappropriate product family mix may result in the increase of bottleneck utilization rate and production cycle time and may decrease delivery performance in consequence. Therefore, bottleneck utilization rate is categorized as an input for production control.
3. *Number of CCR workstation* If the utilization rate of a workstation is over 70% in a planning period, the workstation is treated as a capacity constraint resource (CCR). The more CCR workstations there are in a system, the higher is the probability of bottleneck shifting and the more unstable is the production process. Throughput may be decreased and delivery date may be delayed as a result. Thus, this factor is an input for production control.
4. *Layer cycle time* Layer cycle time measures the duration of time consumed by one photolithography activity and all the steps between the two consecutive photolithography activities. Time constraint characteristic must be considered for processing operations of each layer. For example, furnace activity must be processed in a limited time after the completion of wet etch process; otherwise, this batch of wafers must go through the wet etch process again. As layer cycle time increases, the probability of re-work increases. Not only the production activity control becomes more complicated, yield rate will be impacted. As a result, layer cycle time is an input for production control.
5. *X-Factor* The ratio of production cycle time to theoretical process time for each product. With the prerequisite of satisfying the demand of customers, a lower ratio indicates a faster delivery, and a higher capital turnover rate. X-Factor, therefore, is an input in the financial aspect.
6. *WIP level* The number of lots that has been released into the wafer fab but has not yet been finished processing through all of its manufacturing steps in a period of time. As WIP level increases, more capital is locked, and capital turnover rate decreases in consequence. Therefore, WIP level is an input factor in the financial aspect.
7. *Throughput* The number of lots of production that passes through the final operation step in a period. A higher throughput implies a higher sales revenue and a higher capital turnover rate for the enterprise. Throughput, as a result, is an output in the financial aspect.
8. *Contribution margin* The profitability of a certain product family mix. It is the amount of sales revenue less raw material and indirect variable costs for a period. All finished products are assumed sold. The price for a product is set by its product family, priority rank and the number of layers that product goes through. In a wafer fab, most manufacturing costs are fixed. The indirect variable cost includes cost of all indirect materials and is varied according to the process flow. The higher the contribution margin is, the more productivity the utilization of system resources is, and the more beneficial the operation of the enterprise is. Therefore, contribution margin is an output in the financial aspect.

4.4. System environment

In order to obtain a set of product family mixes that is efficient for the factory to manufacture, actual data is collected from a wafer fabrication factory located on the Science-Based Industrial Park in Taiwan. A simulation model is developed by EM-Plant (Tecnomatix Technologies Ltd., 2001) to generate relevant production performance factors. Simulation results are then applied in the DEA window analysis to convert the performance results under each product family mix over time into an overall efficiency score. To simplify the complexity of the environment, the simulation model built in this paper is based on the following assumptions and limitations:

- There are two different product family types. Product family A consists of a variety of logic products, and product family B consists of memory products. The process of each product family is different and unique.
- Products belonging to family A require 305 operations and pass through the photolithography operation 17 times. Products in family B require 330 operations and pass through the photolithography operation 20 times.
- There are 83 different types of workstations, with 13 6-lot workstations, three 4-lot workstations, and 19 2-lot workstations. Each workstation consists of a given number of identical machines operated in parallel.
- The lot priority is classed into hot, rush and normal in descending order. The ratio of priorities for each product family is set to be 1, 2, and 7 for hot, rush and normal classes, respectively.
- Wafer lot(s) can be released to shop floor only when the same quantity of wafers are finished and transferred out. The releasing batch size for both normal and rush lots is

six lots. Batch machines adopt full batch size policy. Once batch forming is completed, processing sequence is based on the priority class and FIFO rule.

- The hot orders are not limited by batching policy, and they can be released into shop floor and be loaded onto any batch machine with only a single lot.
- Lots with different product types and classes cannot be processed simultaneously.
- The charged price for product with normal priority is set to be \$40 per passing through the photolithography operation for product family A, and \$50 for product family B. Because the waiting time for higher priority orders is shorter than that for normal orders, the charged prices for hot and rush priority products are set to be 150% and 50% mark-up of the price for normal product, respectively.

Table 2
Throughput targets and average throughput outcomes

Product family mix	Monthly throughput target (lot)	420	620	640	464	343	387	526
Mix (2, 8)	Real average throughput target (lot)	423	625	637	468	345	388	525
Mix (3, 7)		420	615	645	469	338	392	529
Mix (4, 6)		424	620	645	466	343	392	530
Mix (5, 5)		420	618	642	465	348	392	525
Mix (6, 4)		423	624	645	465	347	382	523
Mix (7, 3)		419	624	641	462	341	387	529
Mix (8, 2)		425	617	635	459	348	390	524

Table 3
Simulation results for candidate factors under Mix (2, 8)

Year (throughput target)	WIP in front of photolithography workstation (lot)	Throughput (lot)	BN utilization rate	Number of CCR workstations	WIP level (lot)	Layer cycle time (second)	X-factor	Contribution margin (\$)
Year 1 (420 lots)	8	423	0.638	0	187	53,192	1.41	106,149,525
Year 2 (620 lots)	21	625	0.927	8	306	60,043	1.59	156,543,300
Year 3 (640 lots)	26	637	0.963	10	319	61,354	1.63	161,580,325
Year 4 (464 lots)	10	468	0.700	0	206	53,797	1.43	117,118,625
Year 5 (343 lots)	6	345	0.517	0	151	52,422	1.39	86,856,600
Year 6 (387 lots)	8	388	0.577	0	169	52,657	1.40	97,129,975
Year 7 (526 lots)	11	525	0.779	2	236	55,219	1.46	131,401,475

Table 4
Correlation analysis of candidate factors

	Throughput (lot)	BN utilization rate	Number of CCR workstations	WIP Level (lot)	Layer cycle time (second)	X-factor	Contribution margin (\$)
WIP in front of photolithography workstation (lot)	0.94	0.94	0.91	0.97	0.96	0.92	0.85
Throughput (lot)	1.00	1.00	0.82	0.99	0.89	0.85	0.90
BN utilization rate		1.00	0.84	0.99	0.89	0.86	0.91
Number of CCR workstations			1.00	0.88	0.87	0.85	0.82
WIP level (lot)				1.00	0.93	0.91	0.93
Layer cycle time (s)					1.00	0.97	0.83
X-factor						1.00	0.88

Table 5
Input and output factors for evaluation

Factor	Input or Output
Layer cycle time	Input
WIP in front of photolithography workstation	Input
WIP Level	Input
BN utilization rate	Output
Contribution margin	Output
Number of CCR workstations	Input
X-factor	Input

- Direct material cost is set to be $100 per wafer. Indirect material cost, such as photo-resist, special gas, chemical and quartz, is varied according to the production family. The indirect material cost is assumed to be $7.5 per layer for product family A, and $8 per layer for product family B.
- The observation period is seven years, and the throughput target is set to be 420 lots, 620 lots, 640 lots, 464 lots, 343 lots, 387 lots and 526 lots per month for year 1 to year 7, respectively. The window length is fixed to be three years ($K = 3$).
- Product family mixes are set between (2:8) to (8:2). Mix (2:8) means that the product family mix ratio for product family A to product family B is 2 to 8.
- The simulation model is run 15 times to generate statistical results under each *product family mix and each throughput target.*

Table 6
Window analysis of alternatives

Alternatives	Year 1 (420)	Year 2 (620)	Year 3 (640)	Year 4 (464)	Year 5 (343)	Year 6 (387)	Year 7 (526)	Mean (M_l)	Variance (V_l)	TR_l
Mix(2, 8)	1	1	1							
		1	1	1						
			1	1	1					
				1	1	1				
					1	1	0.991	0.9994	0.0006	0.0086
$CR_{1,m}$	X	0	0	0	0	0	X	CR_1	0	
Mix(3, 7)	1	1	0.988							
		1	0.980	1						
			1	1	0.995					
				1	0.995	1				
					0.995	1	1	0.9970	0.0015	0.0199
$CR_{2,m}$	X	0	0.02	0	0	0	X	CR_2	0.0199	
Mix(4, 6)	0.998	1	0.948							
		1	0.945	0.990						
			0.981	0.990	0.973					
				0.990	0.973	0.999				
					0.973	1	1	0.9839	0.0049	0.0549
$CR_{3,m}$	X	0	0.036	0	0	0.001	X	CR_3	0.0358	
Mix(5, 5)	0.960	0.985	0.950							
		0.981	0.950	0.982						
			1	0.981	0.975					
				0.981	0.975	0.969				
					0.978	0.996	0.976	0.9759	0.0038	0.0503
$CR_{4,m}$	X	0.004	0.050	0	0.004	0.027	X	CR_4	0.0503	
Mix (6, 4)	1	1	0.933							
		1	0.931	0.978						
			0.984	0.976	1					
				0.976	1	0.980				
					1	0.987	0.997	0.9828	0.0061	0.0694
$CR_{5,m}$	X	0	0.053	0.001	0	0.007	X	CR_5	0.0530	
Mix (7, 3)	1	1	0.967							
		1	0.967	1						
			1	1	1					
				1	0.990	0.945				
					0.990	0.955	1	0.9877	0.0051	0.0545
$CR_{6,m}$	X	0	0.033	0	0.010	0.010	X	CR_6	0.0327	
Mix (8, 2)	1	0.973	0.966							
		0.973	0.966	1						
			1	1	1					
				1	1	1				
					1	1	1	0.9919	0.0038	0.0340
$CR_{7,m}$	X	0	0.034	0	0	0	X	CR_7	0.0340	

Table 7
Window analysis of the top three alternatives by CCR_d-I and CCR_d-O

Alternatives	Year 1 (420)	Year 2 (620)	Year 3 (640)	Year 4 (464)	Year 5 (343)	Year 6 (387)	Year 7 (526)	Mean (M_l)	Variance (V_l)	TR_l
Mix(2, 8)	1	1	1							
		1	1	1						
			1	1	1					
				1	1	1				
					0.9133	0.9126	0.8879	0.9809	0.0107	0.11208
$CR_{1,m}$	X	0.000	0.000	0.000	0.087	0.087	X	CR_1	0.087	
Mix(3, 7)	0.9834	0.9975	0.9583							
		0.9949	0.9583	0.9929						
			0.9583	0.993	0.9223					
				0.9978	0.9223	0.9834				
					0.8424	0.8975	1	0.9602	0.0123	0.15761
$CR_{2,m}$	X	0.003	0.000	0.005	0.080	0.086	X	CR_2	0.086	
Mix(8, 2)	0.793	0.9731	0.9681							
		0.9731	0.9681	0.7862						
			0.9681	0.7849	0.7753					
				0.7841	0.7753	0.7916				
					0.7081	0.7227	0.9001	0.8448	0.0268	0.26496
$CR_{7,m}$	X	0	0	0.002	0.067	0.069	X	CR_7	0.069	

4.5. Results of window analysis

The data of the candidate factors is obtained from running simulation under the environment of the given throughput target and product family mix. Table 2 shows the monthly throughput targets and average monthly throughput outcomes under different product family mixes in each year. Note that the predetermined throughput targets and the outcomes from the simulation model may not be the same. In order to maintain a fair evaluation, only the simulation results with throughput deviation of less than five batches from the predetermined throughput target are collected. A partial data of the collected candidate factors under different environments is shown in Table 3.

Based on the procedures stated in Section 4.2, a correlation analysis of the factors is done by STATISTICA 6.0 (StatSoft Inc., 1984) to check if there is any factor that has a negative correlation coefficient or perfect positive correlation with other factors. The correlation coefficient of the input and output factors are shown in Table 4. The correlation coefficient between throughput and bottleneck utilization rate is exactly one. Since the correlation coefficients of bottleneck utilization rate with other factors are higher than the coefficients of throughput with other factors, throughput is deleted from the list. The input and output factors selected for evaluation of the wafer fab are listed in Table 5.

With the simulation results of the selected factors, DEA window analysis can be done by Excel Solver via Visual Basic application (Microsoft Company, 2003). In this paper, we assume constant returns to scale; that is, as all inputs double, all outputs will double. The overall efficiency for each DMU is calculated by using CCR_d-I model, and the DEA window analysis is applied. These results are shown in Table 6.

Observing the average efficiency values, Mix (2, 8) is the highest with a mean of 0.9994. On top of that, this product family has the lowest variance of 0.0006. In a highly variant demand changing environment, Mix (2, 8) has a quite stabilized performance over the years.

The second and third best product family mixes are Mix (3, 7) and Mix (8, 2). Both mixes maintain relatively high efficiency over the periods, and their variances are not too big either; therefore, the overall performances of the system under these two mixes are quite stabilized too. Regarding the CR value, the best mix is Mix (2, 8), and the second best is Mix (3, 7). Mix (2, 8) also has the best TR value of 0.0086, followed by Mix (3, 7) and Mix (8, 2).

With the overall evaluation, the best mix is Mix (2, 8), and Mix (3, 7) and Mix (8, 2) perform quite well too. In fact, the performances under Mix (2, 8), Mix (3, 7) and Mix (8, 2) are not significantly different. Therefore, these three mixes are further evaluated. Since financial success is the ultimate goal for an enterprise, only the financial factors, contribution margin, X-factor and WIP level, are considered here, and the results are shown in Table 7.

Under the window analysis of the three product family mixes by focused on financial aspect, Mix (2, 8) and Mix (3, 7) perform well than Mix (8, 2) in efficiency mean, variance and total range. In addition, Mix (2, 8) performs better than both Mix (3, 7) and Mix (8, 2) in all aspects. This implies that if the fab is able to maintain such a product family mix in a long term, it can be competitive and make a very reasonable profit. In the case that the fab need to be flexible in order acceptable, then it should concentrate its product mix in a range from Mix (2, 8) to Mix(3, 7), and preferably Mix (2, 8).

5. Conclusions

In this paper, a DEA window analysis model is established to evaluate product family mixes in a wafer fab. Without assigning weights to any performance indicator, we can use DEA window analysis to evaluate the efficiency of different product family mixes under a long term and obtain a best product family mix that is relatively more efficient for production. The results not only try to maximize the production efficiency and hence the profit, but also considers several other important input and output factors that maintain production smoothing.

A virtual wafer fabricator is first constructed, production with various product family mixes over several periods of time is simulated, and simulation results of critical performance factors are collected. The DEA window analysis is then applied to analyze the results of different product family mixes over time, and the mixes with higher performance are selected. For the selected mixes, another DEA window analysis is run based on a reduced number of factors that are the highest concern of the management, and the most recommended product family mix can be generated as a result. By adopting the proposed mechanism, a semiconductor fabricator can have a guidance regarding strategies for order management and aggregate planning to improve manufacturing efficiency and to be competitive. For the selected product family mix, how to determine the most appropriate priority mix to both satisfy customer demand and meet fab production performance can be our future research direction.

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