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行政院國家科學委員會專題研究計畫 成果報告

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晶圓製造廠產品組合之設定

Product Mix Determination for Semiconductor Fabricator

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行政院國家科學委員會專題研究計畫成果報告

晶圓製造廠產品組合之設定

Product Mix Determination for Semiconductor Fabricator

計書編號: NSC 93-2213-E-216-041

執行期限:93 年 9 月 1 日至 94 年 7 月 31 日

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中文摘要:晶圓製造之高利潤時代已是過去式,如何在此高科技之傳統產業生存以因應市 場之高度競爭,已成為每一晶圓製造廠必須面對的重要課題。因其高投資成本的特性,晶 圓製造廠必須充分利用目前所有的產能,以達最大化利潤及具競爭力,而晶圓製造之複雜 特性亦會影響生產的平穩度。本研究之目的,在於提供產品組合結構設定的有效方法,以 達到最佳化之生產製造。考慮採用的主要方法為層級分析法(AHP)、網路分析法(ANP)及資 料包絡法(DEA)。首先利用層級分析法(AHP)及資料包絡法(DEA),以階層分析投入與產 出過程,並結合Delphi法的專家意見以考慮各要素之重要性,進而獲得最理想產品組合結 構。再應用網路分析法(ANP) 及資料包絡法(DEA),以層級分析法為基礎,增加考慮要素 間之交互作用,來決定優先權重,使晶圓製造業朝著最佳化產品組合結構,獲取最佳的生 產績效與最大的利潤。

關鍵詞:層級分析法、網路分析法、效率、產品組合、晶圓製造

Abstract: The era of high profitability for semiconductor manufacturing is past, and how to survive in a competitive market is a major issue that every semiconductor fabricator must face. Due to the characteristic of high investment cost in semiconductor fabricator, a company needs to fully utilize its current capacity in order to acquire higher profit and be competitive. In addition, the complex manufacturing characteristics in wafer fabrication also have impact on the smoothness of production process. The purpose of this research is to present effective approaches to find a set of product mix for the company to achieve optimal manufacturing. Three methodologies are considered: analytic hierarchy process (AHP), analytic network process (ANP) and data envelopment analysis (DEA). AHP and DEA are incorporated first to analyze the hierarchical inputs and outputs, to combine experts' opinions on the importance of factors through Delphi method, and to obtain the most suitable product mix set. Based on AHP/DEA approach, a combination of ANP and DEA is next taken to consider the interrelationship among factors in the determination of priority weights and to generate advice for a semiconductor fabricator in adopting the most suitable product mix and to obtain the best production performance and highest profitability possible.

Keywords: Analytic Hierarchy Process, Analytic Network Process, Efficiency, Product Mix, Semiconductor Fabricator.

1. INTRODUCTION

Product mix planning is a common problem often encountered in manufacturing, and the topic has gained a tremendous amount of interest in research for more than half of a century. The product mix planning problem in wafer fabrication is a much more difficult problem due to

the complexity of its environment. A very high capital investment in wafer fab plant and equipment is required. An amount of \$US 500 million to 1 billion is needed for the construction of a wafer fab, and the cost is predicted to keep increasing for the foreseeable future. In addition, wafer fabrication involves a very complicated manufacturing system, and its manufacturing process may consist of several hundreds of processing steps on a single wafer and a flow time of usually more than one month. Production performance in semiconductor fabrication is a result of the interaction among equipment set availability, control rules and loading condition. Because the process plan of a product and the requirement of setups can be different depending on the type of products manufactured, different product mix has a different impact to the production performance, and this only complicates the already very complex system. On top of that, performance indicators usually are interrelated that some of them are positively dependent while others are counteractive.

There is no optimum production performance for a fab since different people emphasize in different performance indicators and therefore evaluate production performance differently. For instance, finance people may be interested in the final profit a fab can make; on the other hand, industrial engineers want to generate the maximum throughput and maintain production smoothness. Based on the performance indicators selected, the performance evaluation under a specific product mix will be different. Therefore, the evaluation of different performance indicators which are of the most interest to decision makers is necessary. Due to the many different factors that decision makers would like to either maximize or minimize, linear programming, which is often applied in the search of an optimal product mix in the past, may not be sufficient in wafer fabrication environment. In consequence, a multiple criteria decision-making method (MCDM), which considers the optimization of various factors, is required to organize available data and to provide a singular metric to compare performances for the selection of a suitable product mix.

Analytic hierarchy process (AHP), which generalizes experts' opinion to evaluate alternatives, is a good method to be adopted. Whereas AHP represents a framework with a uni-directional hierarchical relationship, ANP allows for more complex interrelationships among decision levels and attributes. However, there are often many different product mixes that are under consideration, and AHP or ANP alone is too difficult and too cumbersome to be implemented as a result. Data envelopment analysis (DEA) is able to consider more alternatives than AHP or ANP does, but it does not allow decision makers to input their weighting preferences on performance indicators. As a result, this research will propose two product mix selection models to select the most appropriate product mix that most satisfies the performance requirement of decision makers for fabrication: an AHP/DEA model and an ANP/DEA model.

The rest of this paper is organized as follows. Section 2 reviews the decision making tools AHP, ANP and DEA. Section 3 proposes an AHP/DEA model for the selection of product mix. Section 4 proposes an ANP/DEA model for the selection of product mix. In Section 5, some conclusion remarks are made.

1. AHP, ANP AND DEA

2.1. Analytic Hierarchy Process (AHP)

Analytic hierarchy process (AHP) is a mathematically-based MCDM tool, and it has become popular to academic researchers for data analysis, model verifications, and to provide critical information for managers to make business decisions. AHP is originally introduced by Saaty (1980, 1994, 1996) back to the early 1970s in response to the scarce resources allocation and planning needs for the military, and its purpose was to structure a decision process in a scenario influenced by multiple independent factors. A complex problem can be decomposed into several sub-problems in terms of hierarchical levels, and the factors of the same hierarchical level are compared pairwisely relative to their impact on the solution of their higher level factor, and the alternatives are also compared pairwisely in terms of how they perform under each of the lowest-level factors. The application of AHP involves six essential steps (Cheng *et al.*, 1999; Chung *et al.*, to appear; Saaty, 1994; Zahedi, 1986):

- 1. Define the problem and state the objectives and outcomes.
- 2. Decompose the problem into a hierarchical structure with decision elements, including criteria and alternatives.
- 3. Employ pairwise comparisons among decision elements and form comparison matrices.
- 4. Estimate the relative weights of the decision elements using the eigenvalue method.
- 5. Examine whether the judgments of decision makers are consistent by checking the consistency property of matrices.
- 6. Obtain an overall rating for the alternatives by aggregating the relative weights of decision elements.

AHP has been widely used in decision-making in various fields such as political, social, economic and management sciences, and numerous applications have been published in literature (Shim, 1989). In the field of manufacturing, AHP has been used in the areas such as plant location selection (Yu and Li, 2001), justification of flexible manufacturing systems (Chan and Ip, 1995), semiconductor facility layout design process (Padillo *et al.*, 1997; Yang *et al*., 2000), and technology selection (Punniyamoorthy and Ragavan, 2003). Chung *et al.* (to appear) is the first to apply AHP to solve the product mix problem in wafer fabrication; however, as stated before, only a number of product mixes can be evaluated under a simple AHP model in order to limit the total number of pairwise comparisons. How to evaluate numerous product mixes is the objective of this paper.

2.2. Analytic Network Process (ANP)

The ANP, also introduced by Saaty, is a generalization of the AHP (Saaty, 1996). Whereas AHP represents a framework with a uni-directional hierarchical relationship, ANP allows for more complex interrelationships among decision levels and attributes. The ANP feedback approach replaces hierarchies with networks, in which the relationships between levels are not easily represented as higher or lower, dominated or being dominated, directly or indirectly (Meade and Sarkis, 1999). For instance, not only does the importance of the criteria determine the importance of the alternatives as in a hierarchy, but also the importance of the alternatives may have impact on the importance of the criteria (Saaty, 1996). Therefore, a hierarchical structure with a linear top-to-bottom form is not applicable for a complex system. The process of ANP comprises four major steps (Meade and Sarkis, 1999; Saaty, 1996):

- 1. *Model Construction and Problem Structuring* The problem should be stated clearly and decomposed into a rational system like a network.
- 2. *Pairwise Comparisons Matrices and Priority Vectors* In ANP, like AHP, decision elements at each component are compared pairwise with respect to their importance towards their control criterion, and the components themselves are also compared pairwise with respect to their contribution to the goal.
- 3. *Supermatrix Formation* The supermatrix concept is similar to the Markov chain process (Saaty, 1996). To obtain global priorities in a system with interdependent influences, the local priority vectors are entered in the appropriate columns of a matrix, known as a supermatrix. As a result, a supermatrix is actually a partitioned matrix, where each matrix segment represents a relationship between two nodes (components or clusters) in a system (Meade and Sarkis, 1999).
- 4. *Selection of Best Alternatives* Raising a matrix to powers gives the long-term relative influences of the elements on each other. To achieve a convergence on the importance

weights, the weighted supermatrix is raised to the power of $2k+1$, where k is an arbitrarily large number, and this new matrix is called the limit supermatrix (Saaty, 1996). The limit supermatrix has the same form as the weighted supermatrix, but all the columns of the limit supermatrix are the same. By normalizing each block of this supermatrix, the final priorities of all the elements in the matrix can be obtained. The alternative with the largest overall priority should be the one selected.

2.3. Data Envelopment Analysis (DEA)

Data envelopment analysis (DEA) is also a popular MCDM method in recent years. DEA was first introduced in 1978 by Charnes, Cooper and Rhodes to investigate not-for-profit organizations whose success cannot be measured by a single measure, such as profit. DEA is a flexible, nonparametric technique, and it does not require any assumption about the functional form. Based on the observed multiple inputs and outputs of individual decision making units (DMU), an empirical "best practice production frontier" can be estimated (Charnes *et al.*, 1978). The frontier is a piecewise linear envelopment surface and approximates the true production function. The efficiency of a DMU is measured by its position relative to the efficient frontier, and the DMUs that locate on the frontier, the envelopment, are considered to be the most efficient. From the input perspective for a DMU, 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. From the output perspective, if the amount of an output can be increased while the amount of any output does not decrease and the amount of all its inputs does not increase, then the DMU is also inefficient. The theory, development and applications of DEA, as well as its strengths and weaknesses, have been discussed in many papers, and numerous models of DEA have been developed for various applications in the past two decades (Charnes *et al.*, 1994; Cooper *et al.*, 2000).

Although DEA applications were traditionally focused on not-for-profit organizations and government agencies, more and more research works have applied the DEA methodology to the profit oriented sectors in recent years. For example, the DEA method is used by Chang *et al.* (1996) to measure multiple performance criteria for 42 dispatching rules in a job shop environment. Seven performance measures are considered, and the efficiency of each dispatching rule relative to other rules is calculated. Metters *et al.* (1999) apply DEA to inventory policies by considering multiple dimensions of performance, such as cost, service level, and schedule stability. The DEA methodology is extended to aid in the evaluation of the simulation results, where DEA serves to increase the scope of the experimental design. Carbone (2000) adopts DEA methodology to evaluate efficiency areas, including epitaxy, thin films, hot process, etch, implant and photo, within a semiconductor manufacturing fabrication line. With inputs of mean time between failure (MTBF), scrap/1000 wafer moves, cycle time and downtime and outputs of wafer moves, overall equipment efficiency and activity ratio (actual moves/planned moves), the areas of best practice within a semiconductor fabricator can be identified. Chung *et al*. (2002, 2003, 2004) adopt DEA to solve product mix problem in wafer fabrication. However, even though the models do not require a *priori* specification of weights on performance indicators, decision makers do not have a chance to express their opinions either. Therefore, in this paper, we will incorporate the opinions into the product mix selection process.

In this research, CCR, introduced by Charnes, Cooper and Rhodes (1978), is adopted for the DEA analysis. CCR assumes constant returns to scale (CRS); that is, a doubling of all inputs leads to a doubling of all outputs. Under the assumption of CRS, the efficiency results obtained from input-oriented CCR (input minimization in which maximal movement toward the frontier through proportional reduction of inputs is focused) and output-oriented CCR (output maximization in which maximal movement via proportional augmentation of outputs is stressed) are identical.

3. AHP/DEA MODEL FOR PRODUCT MIX SELECTION

In this section, an AHP/DEA model for evaluating the performance under different product mixes in a semiconductor fabricator is proposed. The steps are summarized as follows:

*Step 1***.** Experts in semiconductor industry are invited to define the product mix problem. Since product mix has a great influence on the production system and final financial return for a fab, the selection of an appropriate product mix for a fab to produce is essential for the fab to be successful.

Step 2. Decompose the product mix problem hierarchically. The efficient production performance in a semiconductor fabricator is the overall objective in the first level. The criteria for achieving the overall objective in the second level and detailed criteria in the third level are analyzed and determined by the experts.

Step 3. Based on the hierarchy proposed, formulate a questionnaire to compare criteria pairwisely in their contribution toward achieving the goal of efficient production performance and detailed criteria pairwisely in their contribution toward achieving their upper-level criterion.

Step 4. Form matrices to represent each pairwise comparison for each decision maker. For example, a matrix W for a decision maker can be formed to indicate his/her opinion of the relationship among criteria toward achieving the goal (Alam and Shrabonti, 2002; Saaty, 1980):

$$
C_{I} \begin{bmatrix} C_{1} & C_{2} & \cdots & C_{m} \\ \frac{W_{1}}{W_{1}} & \frac{W_{1}}{W_{2}} & \cdots & \frac{W_{1}}{W_{m}} \\ \frac{W_{2}}{W_{1}} & \frac{W_{2}}{W_{2}} & \cdots & \frac{W_{2}}{W_{m}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ C_{m} \begin{bmatrix} W_{1} & \cdots & W_{m} \\ \frac{W_{1}}{W_{1}} & \frac{W_{2}}{W_{2}} & \cdots & \frac{W_{m}}{W_{m}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ C_{m} \begin{bmatrix} W_{m} & \cdots & W_{m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ W_{m} & \cdots & W_{m} \end{bmatrix} \end{bmatrix} \begin{bmatrix} C_{1} & C_{2} & \cdots & C_{m} \\ C_{2} & C_{2} & \cdots & C_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ C_{m} & C_{m} & C_{m} & \cdots & C_{mm} \end{bmatrix}
$$
(1)

Step 5. Calculate the maximum eigenvalue and eigenvector for each matrix. The formulas for the calculation with matrix W are:

$$
W \cdot w = \lambda_{\text{max}} \cdot w \tag{2}
$$

$$
and w = \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_m \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_m \end{bmatrix}
$$
 (3)

where *w* is the eigenvector, the weight vector, of W, λ_{max} is the largest eigenvalue of W, and *m* is the number of criteria.

Step 6. Check the consistency property of the matrices to ensure consistency of judgments in the pairwise comparison. The consistency index (CI) and consistency ratio (CR) are defined as (Saaty, 1980):

$$
CI = \frac{\lambda_{\text{max}} - m}{m - l}
$$
(4)

$$
CR = \frac{CI}{RI}
$$
(5)

where *m* is the number of items being compared in the matrix, and RI is random index, the average consistency index of randomly generated pairwise comparison matrix of similar size, as shown in Table 1.

In the case that the calculated CR value exceeds the threshold CR values (0.05 for a 3×3 matrix,

0.08 for a 4×4 matrix, and 0.10 for larger matrices), an inconsistent judgment is indicated, and the original values in the pairwise comparison matrix must be revised by the decision maker who makes the comparison (Saaty, 1994).

Step 7. Combine the opinions of experts by the geometric mean method. For a number of *S* experts, the relative importance level between criteria p and criteria q for expert k , $k=1,2,...,s$, can be expressed as $c_{\text{p}qk}$, and the synthetic set representing the relative importance level between factors *p* and *q* can be generated by geometric average as (Kuo *et al.*, 2002):

$$
\eta_{pq} = \left(\prod_{k=1}^{s} c_{pqk}\right)^{\frac{1}{s}}, \forall k=1,2,\ldots,s
$$
\n
$$
\hat{\mathbf{W}} = \begin{bmatrix}\n\eta_{11} & \eta_{12} & \cdots & \eta_{1m} \\
\eta_{21} & \eta_{22} & \cdots & \eta_{2m} \\
\vdots & \vdots & \eta_{pq} & \vdots \\
\eta_{m1} & \eta_{m2} & \cdots & \eta_{mm}\n\end{bmatrix},
$$
\nwhere $\eta_{qp} = \begin{cases}\n\eta_{pq}^{-1}, & \text{if } p \neq q \\
1, & \text{if } p = q\n\end{cases}$ \n(7)

The eigenvector for the group's matrix, \hat{W} , can be obtained by applying the following equations:

$$
\alpha_p = \sum_{q=1}^m \eta_{pq}, \forall p = 1, 2, ..., m
$$
 (8)

$$
Z_p = \frac{\alpha_p}{\sum_{p=1}^m \alpha_p}, \forall p = 1, 2, ..., m
$$
 (9)

Step 8. Aggregate the relative priorities of the decision elements to obtain an overall rating for the lowest-level decision criteria and select a number of factors that have higher priorities. Due to the characteristics of DEA, the number of decision criteria cannot be too many. 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 model becomes smaller, and this makes the discriminating power decrease (Golany, 1989). Therefore, the number of factors selected will be limited by discretion.

Step 9. Construct a virtual wafer fab by building a simulation model. Run this model under different product mixes that are likely to be produced, and collect the data of the factors.

Step 10. Calculate the correlation coefficients among the factors and select the final factors for the DEA analysis. Delete a factor that has a negative correlation with other factors, and select a factor that has higher correlations with the rest of the factors if there are any two or more factors that are perfectly positive correlated.

Step 11. Run DEA analysis to evaluate all product mixes (DMUs) by comparing their data of the final selected factors. Select a number of product mixes that have higher efficiency values for further analysis.

Step 12. Analyze the selected product mixes by AHP again based on the weighting of the factors obtained from decision makers' opinion. In DEA, no *priori* specification of weights is taken

into the model, and the degree of emphasis on the factors by decision makers is therefore not taken into account. In order to incorporate decision makers' opinion into the selection of the most appropriate product mix, AHP is applied in the final selection.

Step 13. Use the simulation data on the factors to form the comparison matrices of alternatives (product mixes) with respect to each factor (lowest-level criterion). Instead of asking decision makers to identify the relative score of the alternatives with respect to each of the factors, simulation data are used to reflect the efficiency of manufacturing since they are objective measures to indicate the manufacturing performance of a fab under different product mixes. Because the unit of measure of simulation data can range from number of lots to hours and to dollars, these quantitative data must be transformed into values between zero to one, and the concept of utility function is adopted. By assigning values of zero and one to the worst and best outcomes, the general formula of a utility linear function of factors is (Clemen, 1996):

$$
u_j(x) = \frac{D - D_j^-}{D_j^+ - D_j^-}
$$
\n(10)

 D_j^+ : The best value of factor *j*.

D^{$⁻$} : The worst value of factor *j*.

D : The value of factor *j* under a certain product mix.

Step 14. Synthesize and establish the final ranking of the product mixes by AHP. The product mix with the highest priority should be selected for production.

4. ANP/DEA MODEL FOR PRODUCT MIX SELECTION

In this section, an ANP/DEA model for evaluating the performance under different product mixes in a semiconductor fabricator is proposed. Some steps are very similar to those for AHP/DEA model. The steps of the model are summarized as follows:

Step 1. Experts in semiconductor industry are invited to define the product mix problem.

Step 2. Decompose the product mix problem into a network. The efficient production performance in a semiconductor fabricator is the overall objective. The criteria for achieving the overall objective in the second level and detailed criteria in the third level are analyzed, and the interrelationship among criteria and detailed criteria are also determined by the experts.

Step 3. Based on the network proposed, formulate a questionnaire to compare criteria pairwisely in their contribution toward achieving the goal of efficient production performance and detailed criteria pairwisely in their contribution toward achieving their upper-level criterion. Interrelationship among criteria and detailed criteria must also be evaluated through the questionnaire.

Step 4. Form matrices to represent each pairwise comparison for each decision maker.

Step 5. Calculate the maximum eigenvalue and eigenvector for each matrix.

Step 6. Check the consistency property of the matrices to ensure consistency of judgments in the pairwise comparison.

Step 7. Combine the opinions of experts by the geometric mean method.

Step 8. Aggregate the relative priorities of the decision elements through ANP to obtain an overall rating for the lowest-level decision criteria and select a number of factors that have higher priorities.

Step 9. Construct a virtual wafer fab by building a simulation model.

Step 11. Run DEA analysis to evaluate all product mixes (DMUs) by comparing their data of the

final selected factors.

Step 12. Analyze the selected product mixes by ANP again based on the weighting of the factors obtained from decision makers' opinion.

Step 13. Use the simulation data on the factors to form the comparison matrices of alternatives (product mixes) with respect to each factor (lowest-level criterion).

Step 14. Synthesize and establish the final ranking of the product mixes by ANP with a supermatrix. The product mix with the highest priority should be selected for production.

This model is very similar to the one in section 3, except that AHP methodology is replaced by ANP methodology.

5. CONCLUSION

Organizing various performance measures to generate a singular metric to compare performances is a challenging task, and semiconductor manufacturing is said to consist of the most complicated production environment comparing to all other industries. In addition, managers may have their own opinion on what performance measures are more important than others. To deal with these problems, a framework that adopts AHP and DEA and a framework that adopts ANP and DEA are presented to evaluate various factors for many different product mixes and to provide relative importance measure for each product mix with the consideration of experts' opinions on the importance weights of performance measures. When the interrelationship among factors is important, the ANP/DEA model should be applied; otherwise, the AHP/DEA model should be adopted for its simplicity. The set of product mix identified can represent a good utilization to the factory capacity, a good performance in production while considering the profitability of the company. The selected product mix can be a reference for production planning and order acceptance. The analysis is aimed at the short-term level and attempts to assess manufacturing performance under various product mixes.

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計畫成果自評

本計畫之相關成果已投稿數篇論文至研討會及 SCI 國際期刊。

可供推廣之研發成果資料表

研發成果推廣單位(如技術移轉中心)。

※ 2.本項研發成果若尚未申請專利,請勿揭露可申請專利之主要內容。

※ 3.本表若不敷使用,請自行影印使用。