Available online at www.sciencedirect.com
ScienceDirect
Expert Systems with Applications 32 (2007) 560–570
Expert Systems with Applications
www.elsevier.com/locate/eswa

Priority mix planning for semiconductor fabrication by fuzzy AHP ranking

He-Yau Kang [a], Amy H.I. Lee [b,*]

[a] *Department of Industrial Engineering and Management, National Chin-Yi Institute of Technology, Taiwan*
[b] *Department of Industrial Management, Chung Hua University, Taiwan*

Abstract

With today's keen competition, semiconductor market has changed from producer-oriented to customer-oriented. To be successful, companies need to consider both customer satisfaction in demand and the ultimate profit goal of companies. Semiconductor fabricators today must face an environment with multi-product types and multi-priority orders. Since semiconductor fabrication has a very complicated production process, the production planning of different products types and priority levels is an even more difficult task to experts. The objective of this study is to construct an analytical approach under a fuzzy subjective judgment environment, in which fuzzy analytic hierarchy process (AHP) method with entropy weight is utilized to deal with uncertainty, to generate performance ranking of different priority mixes. The results provide guidance to experts in a fab regarding strategies for accepting orders with the consideration of manufacturing efficiency in the aspects of *product*, *equipment efficiency* and *finance*.

Keywords: Priority mix; Fuzzy analytic hierarchy process; Entropy weight; Performance ranking; Semiconductor fabrication

1. Introduction

In the construction of a wafer fab, a very high capital investment in plant and equipment, from $US 500 million to 1 billion each, is required. In addition, wafer fabrication involves the most complex manufacturing system among all the manufacturing industries. Production planning of a semiconductor fabricator is very difficult due to its distinctive complexities in the manufacturing process. The process may consist of 300–500 sequential processing operations and a flow time of usually more than twenty days. The production planning and scheduling for the complex manufacturing processes are a challenge due to the factors such as complex product flows, random yields, diverse equipment characteristics, equipment downtime, production and development in shared facilities, data availability and maintenance (Atherton & Atherton, 1995; Uzsoy, Lee, & Martin-Vega, 1992). On top of that, different operations may require the use of the same process equipment, and this is the so-called re-entry characteristic. Thus, a decision made to assign an operation to run on a machine will affect the future demand on this machine, and affect the smoothness of the production flow.

Product mix determination is one of the core problems in current semiconductor production planning system. Different products require different manufacturing processes, and the requirements of setup may also be different. The process plans of products can range from very identical to being extremely distinctive depending on the types of products. The greater is the difference among the process plans, the more diverse are the loading demand and batch difficulty on the factory. In order to best utilize a current fab, a proper selection of product mix is necessary.

Multiple priority levels of orders are usually apparent in wafer fabrication, and higher priority must be given to some urgent lots in order to be competitive and to satisfy customers' demand of accelerating the speed of products entering into the market. When a full loading policy is

* Corresponding author. Tel.: +886 3 518 6582; fax: +886 3 518 6575.
E-mail address: amylee@chu.edu.tw (A.H.I. Lee).

0957-4174/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2006.01.035

not required for batch machines and machines are thus not fully utilized, processing a higher priority order can result in machine capacity loss and a elongation of production cycle time of normal orders is resulted. As the lots with higher priority increase, the variation in shop floor performance will increase and the system throughput will reduce.

In conclusion, product and priority mix has a tremendous impact to the production system, and product mix with different multiple priority lots has different and great influence on the system and pose a great challenge to wafer fabrication. Many performance factors such as cycle time, WIP level, throughput, bottleneck utilization rate will be affected. Organizing the available data is a complicated task, and different people involved in the decision-making may have different opinions on these performance factors. In addition, uncertain thinking process of human beings is present. Therefore, this research proposed a fuzzy AHP model with entropy weight concept to deal with multiple performance factors and to evaluate which product and priority mix can provide a more stabilized production environment and a better overall outcome for a wafer fab. The proposed model can be followed by administrators to determine the most suitable priority mix and can provide a guidance regarding strategies for aggregate planning so as to improve manufacturing efficiency for a fab.

This paper is organized as follows. Section 2 goes over the key concepts of priority levels in production, entropy method and fuzzy AHP. Section 3 presents the methodology and algorithm. Section 4 applies fuzzy AHP based on entropy weights to the evaluation of the efficiency under different priority mixes. Some conclusion remarks are made in the last section.

2. Priority levels in production, entropy method and fuzzy AHP

2.1. Priority levels in production

In order to keep the competitive edge and to satisfy customers' demand of urgent products, a wafer fab often has multiple priority levels of orders. Usually, the production priorities can be divided into three ranks: hot, rush and normal, and a higher priority is given to urgent lots. An order with a higher priority level demands a shorter cycle time, and it can use a machine whenever there is no other higher priority or equal priority order in presence. On the other hand, a lower priority order has to wait till higher priority orders finish processing and the machine becomes available to it. Because of a longer waiting time, the production cycle time of lower priority orders will be elongated as a result.

Some researchers have examined the impact of hot lots to the production system. Ehteshami, Petrakian, and Shabe (1992) proposed that cycle time of a system will remain a constant but the standard deviation of the system will increase sharply when the proportion of hot lots in the fab increases. Further, as the hot lot ratio increases, the average cycle time and the standard deviation of cycle time of normal lots increase sharply.

Atherton and Atherton (1995) stated that a loss in production capacity is resulted by the processing of hot lots due to more complicated process, more process steps, higher reentry frequency and longer processing time. As the number of hot lots increases, a bottleneck shifting may occur, and production planning and capacity assignments will become ineffective.

Fronckowiak, Peikert, and Nishinohara (1996) applied simulation to analyze the impact of different percentages of hot lots on the cycle times and developed a rule in allocating the amount of hot lots to reduce the impact of overall system cycle time. 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.

Since cycle time estimation is the basis for production planning and control, Chung, Lee, and Chuang (2002) developed cycle time estimation algorithms, block-based cycle time (BBCT), for wafer fabs with or without existing engineering lots. The basic logic of the algorithms is to base on the material flow to examine the production cycle time characteristic formation for each lot. Chung, Pearn, Kang, Chen, and Ke (2001) further proposed a block-based cycle time for multiple-priority (BBCT-MP) algorithm to estimate cycle time for the product type with a distinct priority class with the considerations of release size setting, batch policies and dispatching rules for each priority class of products. The proposed algorithm was proved to have an outstanding performance on cycle time and utilization estimation and a quick and satisfactory response.

Chung et al. (2002) constructed a capacity pricing mechanism for wafer fabrication, in which capacity price for each priority of orders is determined by considering the length of cycle time of an order, impact to the cycle time variance of the order, and the usage amount of critical resources. The comprehensive strategies include differentiated price setting for orders of different levels of urgency, analysis of system contribution of order acceptance, and a quick response to the need of emergency order from customers.

Chung, Pearn, Lee, and Ke (2003) presented an effective job order releasing and throughput planning system for multi-priority orders. The system is capable of setting batch policy, estimating cycle time, determining suitable system WIP level, designing daily bottleneck operations, planning release schedule, and setting due date for job orders.

In conclusion, the process of higher priority orders can result in machine capacity loss if a full loading policy is not required for batch machines and machines are not fully utilized. As more orders with higher priorities are processed, the variation in shop floor performance increases, and the system throughput reduces eventually. If bottleneck shifting occurs as a result, the production of lower priority orders will be impacted even more.

2.2. Entropy weight method

Shannon and Weaver (1947) introduced the entropy method to measure the expected information content of certain message, and the method has become an important concept in many fields such as social sciences and physical sciences (Capocelli & De Luca, 1973; Nijkamp, 1997; Shannon & Weaver, 1947). In information theory, entropy is a criterion for the amount of information (or uncertainty) represented by a discrete probability distribution, P_i (Hwang & Yoon, 1981; Jaynes, 1957). A broad distribution represents more uncertainty than a narrowed distribution does. The entropy is expressed by a probability distribution, and the terms "entropy" and "uncertainty" are considered as synonymous (Hwang & Yoon, 1981). The measure of uncertainty was proposed by Shannon as (Chan, Kao, Ng, & Wu, 1999; Hwang & Yoon, 1981; Shannon & Weaver, 1947):

$$S(P_1,\ldots,P_h) = -g\sum_{l=1}^{h} P_l \ln P_l, \tag{1}$$

where $g = 1/\ln(h)$ is a positive constant which guarantees that $0 \leqslant S(P_1,\ldots,P_h) \leqslant 1$. The larger is the value of $S(P_1,\ldots,P_h)$, the less is the information contained in $P_1,\ldots,P_h$. In consequence, 0 entropy indicates that the maximum information (or uncertainty) is contained, and 1 indicates that the minimum information is contained. If all P_l are equal to each other for a given l, that is, $P_l = 1/h$, then $S(P_1,\ldots,P_h)$ takes on its maximum value.

Competitive priority ratings can be obtained through the entropy method (Chan et al., 1999). Let the decision matrix $\mathbf{R}$ of m alternatives and n attributes (criteria) be

$$\mathrm{R} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} B_1 & B_2 & & B_n \end{array} \\ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \end{array} \tag{2}$$

The outcomes, r_{ij}, of alternative A_i and attribute B_j, then can be calculated as following:

$$\mathbf{P} = \begin{bmatrix} \frac{r_{11}}{v_1} & \frac{r_{12}}{v_1} & \cdots & \frac{r_{1n}}{v_1} \\ \frac{r_{21}}{v_2} & \frac{r_{22}}{v_2} & \cdots & \frac{r_{2n}}{v_2} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{r_{m1}}{v_m} & \frac{r_{m2}}{v_m} & \cdots & \frac{r_{mn}}{v_m} \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mn} \end{bmatrix}, \tag{3}$$

where $P_{ij} = r_{ij}/v_i$ and $v_i = \sum_{j=1}^{n} r_{ij}$.

The entropy weight e_i of the set of outcomes of alternatives i can be defined by Eq. (3) as (Cheng, 1996)

$$e_i = -\sum_{j=1}^{n}(p_{ij})\log_2(p_{ij}) \quad \text{for } i = 1,\ldots,m. \tag{4}$$

The normal entropy weight $\hat{e}_i$ of alternatives i can be obtained as

$$\hat{e}_i = \frac{e_i}{\sum_{i=1}^{m} e_i} \quad \text{for } i = 1,\ldots,m. \tag{5}$$

Many researches, from several justified characterizations, have proved that the assessments of attributes' relative importance or priorities can be related very sensibly to this information concept (Chan et al., 1999; Juang & Lee, 1991; Moinpur & Wiley, 1974). Therefore, entropy weight method is adopted in the proposed model in this paper.

2.3. Fuzzy AHP

Many researches have been done to solve multiple criteria decision making (MCDM) problems. For example, Suwignjo, Bititci, and Carrie (2000) constructed a quantitative model for performance measurement system (QMPMS) that relied on AHP to quantify both tangible and intangible factors for performance to let organizations incorporate and map performance measures in a hierarchical way. Bititci, Suwignjo, and Carrie (2001) further applied the QMPMS for manufacturing strategy evaluation and management in a dynamic environment. By adopting the AHP methodology, Wei, Chien, and Wang (2005) presented a comprehensive framework, that "systematically construct the objectives of ERP selection to support the business goals and strategies of an enterprise, identify the appropriate attributes, and set up a consistent evaluation standard for facilitating a group decision process", to select a suitable ERP system. Chung, Lee, and Pearn (2005) proposed an application of the analytic network process (ANP) for the selection of product mix for efficient manufacturing in a semiconductor fabricator by incorporating experts' opinion on various performance factors.

A good decision-making models needs to tolerate vagueness or ambiguity since fuzziness and vagueness are common characteristics in many decision-making problems (Yu, 2002). Since decision-makers often provide uncertain answers rather than precise values, and the transformation of qualitative preferences to point estimates may not be sensible. Linguistic values, whose membership functions are usually characterized by triangular fuzzy numbers, can be used to assess preference ratings instead of conventional numerical equivalence method since the fuzzy linguistic approach can take the optimism/pessimism rating attitude of decision makers into account (Liang & Wang, 1994). Due to the fact that uncertainty should be considered in some or all of the pairwise comparison values, the pairwise comparison under traditional AHP, which needs to select arbitrary values in the process, may not be appropriate (Yu, 2002). The use of fuzzy numbers and linguistic terms may be more suitable, and the fuzzy theory in AHP should be more appropriate and effective than traditional AHP in an uncertain pairwise comparison environment.

One of the most important concepts of fuzzy sets is the concept of an α-cut. For a fuzzy number C and any number $\alpha \in [0,1]$, the α-cut, C_α, is the crisp set (Klir & Yuan, 1995)

$$C_\alpha = \{x \mid C(x) \geqslant \alpha\}. \tag{6}$$

The α-cut of a fuzzy number C is the crisp set C_α that contains all the elements of the universal set U whose membership grades in C are greater than or equal to the specified value of α.

By defining the interval of confidence at level α, the triangular fuzzy number can be characterized as (Cheng, 1996, 1999; Cheng & Mon, 1994; Juang & Lee, 1991; Kaufmann & Gupta, 1991)

$$\widetilde{C}_\alpha = [p^\alpha, s^\alpha] = [(q-p)\alpha + p, -(s-q)\alpha + s], \quad \forall \alpha \in [0,1]. \tag{7}$$

Many methods have been suggested to rank fuzzy numbers, such as intuition ranking method, fuzzy mean and spread, uniform distribution, proportional distribution and α-cut method (Adamo, 1980; Lee & Li, 1988). Adamo (1980) made the definition by selecting a particular value of $\alpha \in [0,1]$ and α-cut $\widetilde{E}_\alpha = [p_e, s_e]$, $\widetilde{F}_\alpha = [p_f, s_f]$, and then $\widetilde{E} \leqslant \widetilde{F}$ if $s_e \leqslant s_f[0]$. This definition is dependent on the chosen value of α, which is usually required to be greater than 0.5. More sophisticated methods such as the use of multiple α-cut values are also present (Mabuchi, 1988). Recently, Chen and Cheng (2005) proposed a metric distance method to deal with the ranking order of fuzzy numbers both for positive and negative, symmetry and non-symmetry fuzzy numbers. A review and comparison of the models were done by some researchers (Chen & Hwang, 1992; Lee & Li, 1988; Zimmermann, 1987). Each method has its own advantages and disadvantages (Klir & Yuan, 1995).

Numerous researches have been done with the application of fuzzy AHP (Boender, de Graan, & Lootsma, 1989; Chen, 1996; Cheng, 1999; Cheng & Mon, 1994; Laarhoeven & Pedrycz, 1983; Murtaza, 2003). There are also several papers that combine AHP, fuzzy theory and entropy method to deal with MCDM problems. Mon, Cheng, and Lu (1995) proposed a model for evaluating weapon systems using fuzzy AHP based on entropy weight. Symmetric triangular fuzzy numbers $\tilde{1}$ to $\tilde{9}$ were used to indicate the relative strength of the elements in the hierarchy, and fuzzy judgment vectors (matrices) through the comparison of performance scores were built next. The priority among the weapon system alternatives could be derived by the entropy weight. Cheng (1996) proposed an algorithm for evaluating naval tactical missile systems by the fuzzy AHP based on grade value of membership function. Membership function of judgment criteria for all subitems was built first, and the grade of membership function by practical data was calculated to represent performance scores. Fuzzy AHP based on entropy was adopted to calculate aggregate weights to deal with naval tactical missile systems valuation and selection problem.

Chan et al. (1999) rated the importance of customer needs in quality function deployment (QFD) by fuzzy and entropy methods. A concise and applicable qualitative description and the corresponding quantitative presentation of the customer needs were generated first. The fuzzy method was next applied to convert customers' linguistic assessments of the needs to fuzzy numbers, and the relative importance of the needs was rated using fuzzy arithmetic. The entropy method was adopted to analyze customers' assessments of the performance of related companies to obtain competitive priority ratings. The above two sets of ratings were combined to generate the final importance ratings of customer needs. Chou and Liang (2001) presented a fuzzy MCDM model for shipping company performance evaluation by combining fuzzy set theory, AHP and concept of entropy. The AHP was first used to construct subjective weights for criteria and subcriteria, and linguistic values represented by triangular fuzzy number were used to evaluate subjective criteria. Financial performance criteria were transformed into trapezoidal fuzzy numbers, while the objective weights for financial subcriteria were obtained by entropy weighting method. The aggregation fuzzy assessment of different shipping companies was synthesized to rank the company performances. Kwong and Bai (2003) proposed a fuzzy AHP with an extent analysis approach to determine the importance weights for the customer requirements in QFD, and stated that the method was effective due to its capability to capture the vagueness of human judgment. The algorithm is simple to determine the weight vectors and easy to implement since the tedious calculation of eigenvectors required by the conventional AHP is no longer necessary.

Lee, Kang, and Wang (in press) constructed an analytical approach for dealing with the priority mix problem under subjective judgment environment, and fuzzy AHP was applied to deal with uncertainty while considering various important factors for efficient semiconductor fabrication. However, the research was rather rough, and the information content of message and the degree of optimism of experts were not considered. As a result, we will propose a more comprehensive model that combines the AHP, fuzzy set theory and entropy method, to solve the priority mix problem in semiconductor manufacturing.

3. Methodology and algorithm

In this section, a systematic fuzzy AHP model with entropy method for evaluating the performance under different priority mixes in a semiconductor fabricator is proposed. The steps are summarized as follows:

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

Step 2. Decompose the priority 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 by the experts.

Step 3. Based on the hierarchy proposed, formulate a questionnaire to first compare criteria pairwisely in their contribution toward achieving the goal of efficient production performance and next compare detailed criteria pairwisely in their contribution toward achieving their upper-level criterion. Five different levels of evaluation are used, and the linguistic values can be obtained from Table 1.

Step 4. Establish fuzzy weight vector. The geometric mean method was adopted to generalize the opinion of experts. For a number of ***T*** experts, the relative importance level between factor P and factor q rated by expert k, $k = 1, 2, \ldots, t$, can be expressed as η_{pqk}, and the synthetic fuzzy set representing the relative importance level between factors p and q can be expressed as (Kuo, Chi, & Kao, 2002)

$$\eta_{pq} = \left(\prod_{k=1}^{t} \eta_{pqk}\right)^{\frac{1}{t}}, \quad \forall k = 1, 2, \ldots, t, \tag{8}$$

$$\mathbf{Q} = \begin{bmatrix} \eta_{11} & \eta_{12} & \cdots & \eta_{1z} \\ \eta_{21} & \eta_{22} & \cdots & \eta_{2z} \\ \vdots & \vdots & \eta_{pq} & \vdots \\ \eta_{z1} & \eta_{z2} & \cdots & \eta_{zz} \end{bmatrix} \tag{9}$$

where $\eta_{qp} = \begin{cases} \eta_{pq}^{-1} & \text{if } p \neq q, \\ 1 & \text{if } p = q, \end{cases}$

$$\alpha_p = \sum_{q=1}^{z} \eta_{pq}, \quad \forall p = 1, 2, \ldots, z, \tag{10}$$

$$Z_p = \frac{\alpha_p}{\sum_{p=1}^{n} \alpha_p}, \quad \forall p = 1, 2, \ldots, z. \tag{11}$$

By synthesizing experts' opinions, the weights of criteria, can be represented by a fuzzy weight vector $\tilde{\mathbf{w}}$:

$$\tilde{\mathbf{w}} = \begin{bmatrix} \tilde{w}_1 \\ \tilde{w}_2 \\ \vdots \\ \tilde{w}_n \end{bmatrix} \tag{12}$$

where $\tilde{w}_p = \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$.

Step 5. Establish judgment vector for each detailed criterion that use simulation results. Both simulation results and experts' opinions are used to estimate the performance of detailed criteria under each priority mix. For simulation results, the unit of measure can range from number of lots to hours and to dollars, these quantitative data need to be transformed into values between zero to one. Membership function is applied here, and "1" represents the best outcome while "0" represents the worst outcome. The membership function for a detailed criterion that is better with a bigger value is as follows:

$$\mu_\theta = \begin{cases} (x - x_\theta^-)/(x_\theta^+ - x_\theta^-), & x_\theta^- \leqslant x \leqslant x_\theta^+, \\ 1, & x \geqslant x_\theta^+. \end{cases} \tag{13}$$

The membership function for a detailed criterion that is better with a smaller value is as follows:

$$\mu_\theta = \begin{cases} (x_\theta^+ - x)/(x_\theta^+ - x_\theta^-), & x_\theta^- \leqslant x \leqslant x_\theta^+, \\ 1, & x \leqslant x_\theta^-, \end{cases} \tag{14}$$

where x_θ^+ is the largest possible value of a detailed criterion, x_θ^- is the smallest possible value of a detailed criterion, and x is the value of a detailed criterion.

Step 6. Establish judgment vector for each detailed criterion that is evaluated by the experts. Some detailed criteria may be difficult to be obtained through simulation, and experts' opinions are, therefore, used instead. Five different levels of evaluation are used and their linguistic values are similar to those shown in Table 1, except that the fuzzy language is changed to "very good", "good", "fair", "poor" and "very poor". The geometric mean method was again used to generalize the opinions of experts. To be consistent with the results obtained from simulation, the geometric mean result for each detailed criterion under each priority mix is minus one and divided by 8. The judgment vector for each qualitative detailed criterion is obtained.

Step 7. Combine the judgment vectors of detailed criteria with the same upper-level criterion with the results from Steps 5 and 6 to obtain transformed values for detailed criteria with the same upper-level criterion. A fuzzy judgment matrix, $\tilde{\mathbf{X}}$, is built next to represent the relative performance of the priority mixes under different criteria.

Table 1
Linguistic value table

Fuzzy language	Quantitative value
Very important	9
Important	7
Equal important	5
Unimportant	3
Very unimportant	1

Step 8. Establish the total fuzzy judgment matrix, $\widetilde{\mathbf{R}}$, by multiplying the elements in fuzzy judgment matrix $\widetilde{\mathbf{X}}$ with the elements in fuzzy vector $\tilde{\mathbf{w}}$. The equation is

$$\widetilde{\mathbf{R}} = \begin{bmatrix} \tilde{x}_{11} \otimes \tilde{w}_1 & \tilde{x}_{12} \otimes \tilde{w}_2 & \cdots & \tilde{x}_{1n} \otimes \tilde{w}_n \\ \tilde{x}_{21} \otimes \tilde{w}_1 & \tilde{x}_{22} \otimes \tilde{w}_2 & \cdots & \tilde{x}_{2n} \otimes \tilde{w}_n \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} \otimes \tilde{w}_1 & \tilde{x}_{m2} \otimes \tilde{w}_2 & \cdots & \tilde{x}_{mn} \otimes \tilde{w}_n \end{bmatrix}. \tag{15}$$

Step 9. Establish the total fuzzy judgment matrix with α-cuts by performing fuzzy number multiplications and additions with the interval arithmetic and cuts. From Eq. (7), Eq. (15) can be simplified to

$$\widetilde{\mathbf{R}}_\alpha = \begin{bmatrix} [r^\alpha_{11L}, r^\alpha_{11U}] & [r^\alpha_{12L}, r^\alpha_{12U}] & \cdots & [r^\alpha_{1nL}, r^\alpha_{1nU}] \\ [r^\alpha_{21L}, r^\alpha_{21U}] & [r^\alpha_{22L}, r^\alpha_{22U}] & \cdots & [r^\alpha_{2nL}, r^\alpha_{2nU}] \\ \vdots & \vdots & \vdots & \vdots \\ [r^\alpha_{m1L}, r^\alpha_{m1U}] & [r^\alpha_{m2L}, r^\alpha_{m2U}] & \cdots & [r^\alpha_{mnL}, r^\alpha_{mnU}] \end{bmatrix}, \tag{16}$$

where $r^\alpha_{ijL} = x^\alpha_{ijL} \otimes w^\alpha_{iL}$, $r^\alpha_{ijU} = x^\alpha_{ijU} \otimes w^\alpha_{iU}$ for $0 < \alpha \leqslant 1$ and for all i, j.

Step 10. Establish the total fuzzy judgment matrix with α-cuts and the degree of satisfaction of the experts on judgment, $\widehat{\mathbf{R}}^\beta_\alpha$. When α is fixed, the index of optimism β can be set to represent the degree of the optimism of a decision maker. A larger β indicates a higher degree of optimism, and vice versa. The index of optimism is a linear convex combination and is defined as

$$\hat{r}^{\alpha\beta}_{ij} = (1-\beta) r^\alpha_{ijL} + \beta r^\alpha_{ijU}, \quad \forall \beta \in [0, 1]. \tag{17}$$

Thus the total fuzzy judgment matrix with α-cuts and index of optimism β is

$$\widehat{\mathbf{R}}^\beta_\alpha = \begin{bmatrix} \hat{r}^{\alpha\beta}_{11} & \hat{r}^{\alpha\beta}_{12} & \cdots & \hat{r}^{\alpha\beta}_{1n} \\ \hat{r}^{\alpha\beta}_{21} & \hat{r}^{\alpha\beta}_{22} & \cdots & \hat{r}^{\alpha\beta}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \hat{r}^{\alpha\beta}_{m1} & \hat{r}^{\alpha\beta}_{m2} & \cdots & \hat{r}^{\alpha\beta}_{mn} \end{bmatrix}. \tag{18}$$

Step 11. Compute the entropy weight e_i of alternative i by applying Eqs. (3) and (4). Then, obtain the normal entropy weight $\hat{e}_i$ of alternative i by Eq. (5).

4. Numerical example

In this section, the proposed fuzzy AHP model is applied to solve the priority mix problem for a fab. In a multi-criteria problem, numerous criteria are considered, and the selection of criteria should be based on the analysis of the specific requirements of the problem. With a comprehensive review of literature and a consultation with domain experts, the hierarchy and the factors for determining the efficiency of priority mix are as in Fig. 1.

The three major criteria and the detailed criteria used to evaluate manufacturing performance of a semiconductor fab are defined as follows:

(1) *Product* evaluates how products are manufactured in a fab.
   - *WIP* measures the number of lots of manufacturing that have been released into the wafer fab but have not yet been finished processing through all of their manufacturing steps.
   - *Throughput* represents the number of lots of manufacturing that pass through the final operation step in a period.
   - *Total layers* count the number of layers the bottleneck processed in a period of time.
   - *Total cycle time* is the duration of time, expressed in hours, consumed by a unit of manufacturing from the time of release into the fab until time of exit from the fab. It is a weighted average cycle time, with the weights being the ratio of product and priority mix.
   - *On time delivery* indicates the ability to meet production schedules. It is calculated by dividing the percentage of actual output quantity by the end of a period that is greater than or equal to the scheduled quantity in a period of time, to the scheduled output in that period of time. It can be expressed at the die level or at the finished goods level (Leachman & Hodges, 1996).
   - *Lateness variance* states the deviation between an order's completion time and its due date. If an order is completed after its due date, it will have a positive lateness. On the other hand, if it is completed before its due date, it will have a negative lateness. A greater lateness variance indicates a higher uncertainty of completing orders on the right time.
   - *WIP turnover* is the replacing rate of WIP during a period. It shows how often the inventory of WIP is replaced during the period being measured. It is calculated by dividing the finished units out by the average WIP (SEMI, 2002).
   - *Cycle time standard variation* expresses the variability of cycle time in the production process. A higher value indicates a higher difficulty in the prediction of the cycle time and a more unstable production system.
   - *Critical WIP* measures the WIP level of the bottleneck resource. It is the WIP level that (theoretically) allows the factory to have the highest throughput rate with the shortest cycle time.

(2) *Equipment efficiency* measures how effective the equipment is used in manufacturing.
   - *BN utilization* measures the average utilization rate of the bottleneck in the system for a period of time. Equipment utilization should be as high as possible at the bottleneck workstation since the bottleneck gates the throughput of the entire manufacturing system.

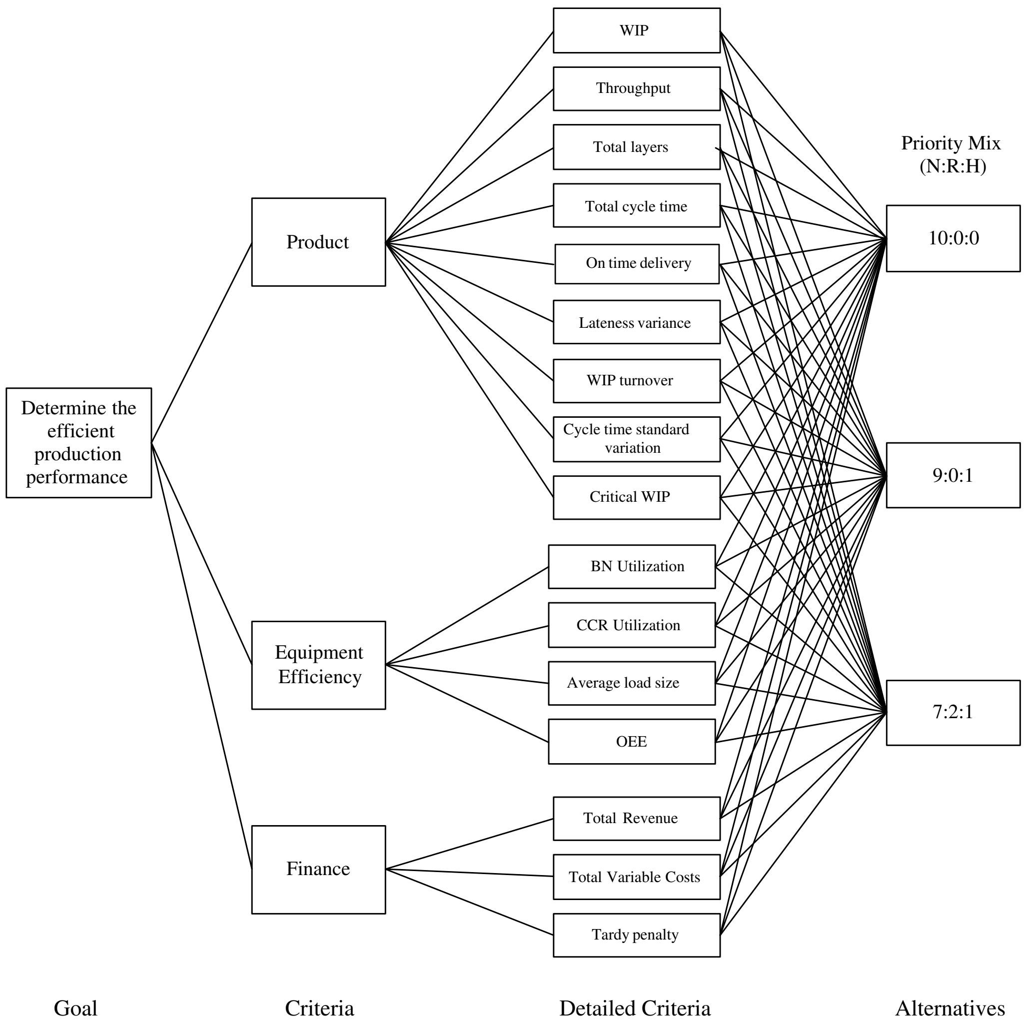

Fig. 1. The hierarchical framework of factors.

- *CCR utilization* shows the average utilization rate of the CCR in the system for a period of time. A CCR is a workstation with a substantially high utilization rate, even though it is not a bottleneck.
- *Average load size* measures the average loading rate on batch equipment. It represents the average number of lots batch equipment can process at a point of time.
- *Overall equipment efficiency* (*OEE*) measures the equipment performance relative to theoretical production time. It is calculated by dividing the theoretical production time for the effective unit output by the total time (SEMI, 2002).

(3) *Finance* evaluates the cash flow a wafer fab can make or need to spend in the manufacturing process.

- *Total revenue* is calculated by summing up revenue of each product type. The price for a product is set by its product type, priority level and the number of layers that product goes through, and revenue of a product is calculated by multiplying the price of the product with its throughput.
- *Variable costs* include total variable manufacturing costs and total holding costs. Direct material cost is the primary part of total variable manufacturing costs. Other variable manufacturing cost includes indirect material cost and is varied according to the manufacturing level. The holding cost is the time cost of carrying WIP in the manufacturing system.
- *Tardy penalty* measures the cost of not meeting due dates. A certain amount of discount or penalty may need to be given to the customers if the completion time of an order is after the contracted due date. In addition, the deterioration of goodwill must be considered.

A questionnaire was constructed and targeted on the experts in the semiconductor industry. A total of six experts are invited to contribute their professional experience. Four of them are senior managers of production planning and finance departments from three internationally well known semiconductor manufacturing companies in the Science-Based Industrial Park in Taiwan, and the other two are scholars in production management from two universities in Taiwan. The first question, "which criteria should be emphasized more in determining efficient manufacturing, and how much more?" was asked, and a pairwise comparison with the fuzzy language in Table 1 was used by experts to express their opinions. The group's opinions can be synthesized by applying Eqs. (8)–(12), and a fuzzy weight vector $\tilde{\mathbf{w}}$ can be obtained where $\tilde{w}_p = \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$. The weight of *product*, *equipment efficiency* and *finance* represented by a fuzzy weight vector $\tilde{\mathbf{w}}$ is

$$\tilde{\mathbf{w}} = \begin{bmatrix} \textit{product} & \textit{equipment efficiency} & \textit{finance} \\ \tilde{3} & \tilde{1} & \tilde{9} \end{bmatrix}.$$

Based on the experts' judgments, *finance* is the most important criterion followed by *product*. Therefore, profitability is the major concern for selecting a product mix.

To obtain a priority mix that is efficient for manufacturing, 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 quantitative production performance indicators. To simplify the complexity of the environment for analysis, we made the following assumptions:

- Two different product types, L and M, are fabricated in this system. Product L is a logic product, and product M is a memory product. The process of each product is different and unique. Product L requires 276 operations and passes through the bottleneck 16 times, or 17 layers are processed. Product M requires 330 operations and passes through the bottleneck 21 times (22 layers processed).
- The lot priority is classed into hot, rush and normal in descending order. Processing a higher priority lot may result in the loss of machine capacity if non-full loading policy is adopted for batch machines. A higher ratio of higher priority lots thus incurs longer waiting time for lower priority lots. Three alternatives are evaluated here: producing only normal products, producing 10% of hot lots and 90% of normal products for each product type, and producing 10% of hot lots, 20% of rush lots and 70% of normal lots for each product type.
- The releasing batch size for normal lots is six lots, and that for hot lots is one lot. 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. For normal lots, a full batch of six lots must be formed before releasing to the floor in order to have effective use of many workstations which have a maximum batch size (MBS) of six lots. For rush orders, the batch size is determined by the minimum batch size of the machine being worked on while the minimum batch size of a machine can be varied from one lot to six lots depending on the machine setting. Wafer lots are released under a fixed work-in process (WIP) policy, CONstant WIP (CONWIP).
- The planning horizon is 168 working days, and each day consists of 24 working hours. The first 84 days are a warm-up period, and the results of the next 84 days are collected. The simulation model is run 15 times to generate statistical results under each product and priority mix. Mix(7:2:l) means that the priority mix ratio for normal, rush and hot levels for both product L and product M are 7, 2 and 1.

Table 2
Simulation result

	Rank mix (N:R:H)			Membership function
	I:Mix(10:0:0)	II:MIX(9:0:1)	III:MIX(7:2:1)	
WIP (lots)	278.71	309.63	279.73	$\mu_{\mathrm{WIP}} = \begin{cases} (400-x)/150, & 250 \leqslant x \leqslant 400 \\ 1, & x \leqslant 250 \end{cases}$
Throughput (TP) (lots)	640	600	620	$\mu_{\mathrm{TP}} = \begin{cases} (x-500)/200, & 500 \leqslant x \leqslant 700 \\ 1, & x \geqslant 700 \end{cases}$
Total layers (TL)	12160	11400	11780	$\mu_{\mathrm{TL}} = \begin{cases} (x-10000)/4000, & 10000 \leqslant x \leqslant 14000 \\ 1, & x \geqslant 14000 \end{cases}$
Total cycle time (CT) (hours)	292.63	346.86	303.21	$\mu_{\mathrm{CT}} = \begin{cases} (400-x)/200, & 200 \leqslant x \leqslant 400 \\ 1, & x \leqslant 200 \end{cases}$
BN utilization (BU) (%)	0.99	0.94	0.97	$\mu_{\mathrm{BU}} = \begin{cases} (x-0.69)/0.3, & 0.69 \leqslant x \leqslant 0.99 \\ 1, & x \geqslant 0.99 \end{cases}$
CCR utilization (CU) (%)	0.83	0.87	0.90	$\mu_{\mathrm{CU}} = \begin{cases} (x-0.5)/0.49, & 0.50 \leqslant x \leqslant 0.99 \\ 1, & x \geqslant 0.99 \end{cases}$
Total revenue (TR) (10^3\$)	16248	15994	17156	$\mu_{\mathrm{TR}} = \begin{cases} (x-15000)/3000, & 15000 \leqslant x \leqslant 18000 \\ 1, & x \geqslant 18000 \end{cases}$
Variable costs (VC) (10^3\$)	3909	3666	3787	$\mu_{\mathrm{VC}} = \begin{cases} (4000-x)/500, & 3500 \leqslant x \leqslant 4000 \\ 1, & x \leqslant 3500 \end{cases}$

The data obtained from running simulation is shown in Table 2. The concept of membership function is used to transform the data into values between zero and one. The membership functions of detailed criteria are listed in Table 2 to assign values of zero and one to the worst and the best outcomes, and the judgment vectors for qualitative detailed criteria are obtained.

Although simulation results can be used to estimate the manufacturing performance, data of many factors are very hard to be obtained through simulation, even if possible. Therefore, some important factors are evaluated by the experts instead. Depending on the availability of data, either data collected from the floor or the opinions given by experts can be analyzed in real practice. Five different levels of evaluation are used here, namely, very good, good, fair, poor and very poor. Group's opinions are generated by geometric average method and are shown in Table 3.

Priority mix I is assessed by experts to perform pretty well on factors such as on time delivery, tardy penalty and cycle time standard variation due to the facts that only normal products are produced and that the environment is most stable with little unexpectedness. The performance of priority mix III is perceived to be relatively better than priority II in many aspects even though three priority levels of products are produced under priority mix III, compared with only hot and normal orders under priority mix II. The major reason for the expected outcomes is because of the batch size of rush orders. In the setting of the production system, the batch size of normal lots is six lots, that is, a full batch of six lots must be formed before it can be released to the floor. On the other hand, the batch size of rush lots can range from one to six lots, depending on the minimum batch size of the machine being worked on. In consequence, the waiting time under priority mix III is lower, and the factors such as cycle time, cycle time standard variation and lateness variance are considerably better. However, the evaluation may change if the batch sizes of the three priorities of orders are set differently from those set in this model.

Each value in Table 3 is minus one and divided by 8, and the judgment vectors for qualitative detailed criteria are obtained. By combining the judgment vectors for both qualitative detailed criteria and quantitative detailed criteria, the transformed values for detailed criteria with the same upper-level criterion (*product*, *equipment efficiency* and *finance*) are listed in Table 4–6.

Table 3
Geometric average of experts' opinion on factors

	Priority mix (N:R:H)		
	I:Mix(10:0:0)	II:Mix(9:0:1)	III:Mix(7:2:1)
On time delivery	8.63	5.14	5.59
Lateness variance	6.90	1.44	5.59
WIP turnover	6.26	2.72	4.86
Cycle time standard variation	7.83	1.20	7.30
Critical WIP	1.44	5.59	5.83
Average load size	4.86	2.72	7.62
OEE	6.90	3.56	8.63
Tardy penalty	8.28	3.56	7.94

By using the total score for each priority mix under each criterion, a fuzzy number is given to represent the relative performance of each priority mix on each criterion. A fuzzy judgment matrix is resulted:

$$\widetilde{\mathbf{X}} = \begin{bmatrix} \tilde{9} & \tilde{3} & \tilde{3} \\ \tilde{1} & \tilde{1} & \tilde{1} \\ \tilde{7} & \tilde{5} & \tilde{3} \end{bmatrix}.$$

Total fuzzy judgment matrix, $\widetilde{\mathbf{R}}$, is

$$\widetilde{\mathbf{R}} = \begin{bmatrix} \tilde{9}\otimes\tilde{3} & \tilde{3}\otimes\tilde{1} & \tilde{3}\otimes\tilde{9} \\ \tilde{1}\otimes\tilde{3} & \tilde{1}\otimes\tilde{1} & \tilde{1}\otimes\tilde{9} \\ \tilde{7}\otimes\tilde{3} & \tilde{5}\otimes\tilde{1} & \tilde{3}\otimes\tilde{9} \end{bmatrix}.$$

By applying Steps 9–11 in Section 3, the performance of different priority mixes under different α-cuts and index of optimism β are calculated and shown in Fig. 2 and Table 7. The results are variant depending on the values of α and β. For example, when we let $\alpha = 0$, as β increases from 0.0 (very pessimistic) to 1.0 (very optimistic), the best alterna-

Table 4
Transformed values for detailed criteria under *product*

	Item	I:Mix(10:0:0)	II:Mix(9:0:1)	III:Mix(7:2:1)
1	WIP	0.81	0.60	0.80
2	Throughput (TP)	0.70	0.50	0.60
3	Total layers (TL)	0.54	0.35	0.45
4	Total cycle time (CT)	0.54	0.27	0.48
5	On time delivery	0.95	0.52	0.57
6	Lateness variance	0.74	0.06	0.57
7	WIP turnover	0.66	0.22	0.48
8	Cycle time standard variation	0.85	0.03	0.79
9	Critical WIP	0.06	0.57	0.60
	Total score	5.85	3.11	5.35

Table 5
Transformed values for detailed criteria under *equipment efficiency*

	Item	I:Mix(10:0:0)	II:Mix(9:0:1)	III:Mix(7:2:1)
1	BN utilization (BU)	1.00	0.83	0.93
2	CCR utilization (CU)	0.67	0.76	0.82
3	Average load size	0.48	0.22	0.83
4	OEE	0.74	0.32	0.95
	Total score	2.89	2.13	3.53

Table 6
Transformed values for detailed criteria under *finance*

	Item	I:Mix(10:0:0)	II:Mix(9:0:1)	III:Mix(7:2:1)
1	Total revenue (TR)	0.42	0.33	0.72
2	Variable costs (VC)	0.82	0.33	0.57
3	Tardy penalty	0.91	0.32	0.87
	Total score	2.15	0.98	2.16

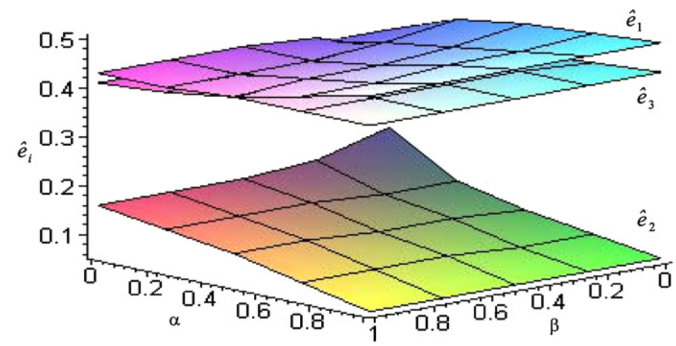

Fig. 2. The curves of entropy weight for priority mix I, II and III with $\alpha = 0.0\ (0.25)\ 1$ and $\beta = 0.0\ (0.25)\ 1$.

Table 7
Performance of priority mixes under different α-cuts and β

β	$\hat{e}_i$	α				
		0.0	0.25	0.5	0.75	1.0
0.00	$\hat{e}_1$	0.41	0.46	0.48	0.49	0.50
	$\hat{e}_2$	0.21	0.13	0.10	0.08	0.06
	$\hat{e}_3$	0.38	0.41	0.42	0.43	0.44
0.25	$\hat{e}_1$	0.41	0.44	0.46	0.48	0.50
	$\hat{e}_2$	0.17	0.13	0.11	0.08	0.06
	$\hat{e}_3$	0.42	0.43	0.43	0.44	0.44
0.5	$\hat{e}_1$	0.41	0.43	0.45	0.48	0.50
	$\hat{e}_2$	0.16	0.14	0.11	0.09	0.06
	$\hat{e}_3$	0.43	0.43	0.43	0.44	0.44
0.75	$\hat{e}_1$	0.41	0.43	0.45	0.47	0.50
	$\hat{e}_2$	0.16	0.14	0.12	0.09	0.06
	$\hat{e}_3$	0.43	0.43	0.44	0.44	0.44
1.0	$\hat{e}_1$	0.41	0.42	0.44	0.47	0.50
	$\hat{e}_2$	0.16	0.14	0.12	0.09	0.06
	$\hat{e}_3$	0.43	0.43	0.44	0.44	0.44

tive changes from mix I with $\hat{e}_1 = 0.41$ (mix III with $\hat{e}_3 = 0.38$) when $\beta = 0$ to mix III with $\hat{e}_3 = 0.43$ (mix I with $\hat{e}_1 = 0.41$) when $\beta = 1$. This implies that when the experts are very undetermined about their evaluations and the simulation results are not very certain, the best alternative may change depending on the experts' level of optimism. On the other hand, as α increases, the best alternative under different levels of β tends to be mix I. From Fig. 2, we can also notice that the surfaces of $\hat{e}_1$ and $\hat{e}_3$ are intersected. As a result, the best alternative can be either mix I or mix III, depending on the values of α and β. However, since α is usually set to be greater than 0.5 in practice, the best alternative is mix I, in which only normal orders are processed. This implies that the fab should stress on producing normal orders and reduce its acceptance of hot or rush orders if possible.

5. Conclusions

Wafer fabrication consists of a very complex production environment, and the priority level issue complicates the production system even more. The aim of this research is to construct a fuzzy AHP model that applies fuzzy set theory and entropy weight concept, to evaluate different priority mixes and to support the selection of priority mix that is efficient for a wafer fab to manufacture.

In the performance evaluation of wafer fabrication, many factors, including financial success for an enterprise, production outcome and smoothness, and equipment utilization, must all be considered. In addition, some factors are quantitative, while others are qualitative. The combination of these factors to generate a final evaluation ranking for different priority mixes is the objective of the proposed model. The importance of the factors is first evaluated by experts, and the uncertainty of human decision-making is taken into account through the fuzzy concept. The outcomes of quantitative factors under different priority mixes are obtained through a simulation model, while the outcomes of qualitative factors under different priority mixes are examined by experts. Fuzzy set theory, entropy weight concept and level of optimism are applied to determine the relative efficiencies of different priority mixes.

In this paper, priority mixes with hot, rush and normal orders are considered. To simplify the model, two products with a fixed product mix ratio are taken into account. However, in this intensive competitive semiconductor industry, many different products with multiple priorities are usually manufactured in order to satisfy customer demand. As a result, the manufacturing environment is even more complex, and this is our future research direction.

Acknowledgement

This research is supported in part by Grant NSC 93-2416-H-167-006 and CHU-94-M-013.

References

Adamo, J. M. (1980). Fuzzy decision trees. *Fuzzy Sets and Systems, 4*(3), 207–220.

Atherton, L. F., & Atherton, R. W. (1995). *Wafer fabrication: Factory performance and analysis*. Boston: Kluwer Academic Publishers.

Bititci, U. S., Suwignjo, P., & Carrie, A. S. (2001). Strategy management through quantitative performance measurement systems. *International Journal of Production Economics, 69*, 15–22.

Boender, C. G. E., de Graan, J. G., & Lootsma, F. A. (1989). Multiple-criteria decision analysis with fuzzy pairwise comparisons. *Fuzzy Sets and Systems, 29*, 133–143.

Capocelli, R. M., & De Luca, A. (1973). Fuzzy sets and decision theory. *Information and Control, 23*(5), 446–473.

Chan, L. K., Kao, H. P., Ng, A., & Wu, M. L. (1999). Rating the importance of customer needs in quality function deployment by fuzzy and entropy methods. *International Journal of Production Research, 37*(11), 2499–2518.

Chen, S. M. (1996). Evaluating weapon systems using fuzzy arithmetic operations. *Fuzzy Sets and Systems, 77*, 265–276.

Chen, L. S., & Cheng, C. H. (2005). Selecting IS personnel use fuzzy GDSS based on metric distance method. *European Journal of Operational Research, 160*, 8003–8820.

Chen, S. J., & Hwang, C. L. (1992). Fuzzy multiple attribute decision making methods and applications. *Lecture notes in economics and mathematical systems*. Berlin: Springer.

Cheng, C. H. (1996). Evaluating naval tactical missile systems by fuzzy AHP based on the grade value of membership function. *European Journal of Operational Research, 96*, 343–350.

Cheng, C. H. (1999). Evaluating weapon systems using ranking fuzzy numbers. *Fuzzy Sets and Systems, 107*, 25–35.

Cheng, C. H., & Mon, D. L. (1994). Evaluating weapon system by analytical hierarchy process based on fuzzy scales. *Fuzzy Sets and Systems, 63*, 1–10.

Chou, T. Y., & Liang, G. S. (2001). Application of a fuzzy multi-criteria decision-making model for shipping company performance evaluation. *Maritime Policy and Management, 28*(4), 375–392.

Chung, S. H., Lee, A. H. I., & Chuang, C. C. (2002). The construction of capacity pricing mechanism in wafer fabrication. In *2002 Asia-Pacific Industrial Engineering and Management Symposium, Taipei*.

Chung, S. H., Lee, A. H. I., & Pearn, W. L. (2005). Analytic network process (ANP) approach for product mix planning in semiconductor fabricator. *International Journal of Production Economics, 96*(1), 15–36.

Chung, S. H., Pearn, W. L., Kang, H. Y., Chen, C. C., & Ke, W. T. (2001). Cycle time estimation for wafer fabrication with multiple-priority orders. In *2001 Advanced Simulated Technologies Conference*. Seattle, WA: The Society for Modeling and Simulation International.

Chung, S. H., Pearn, W. L., Lee, A. H. I., & Ke, W. T. (2003). Job order releasing and throughput planning for multiple-priority orders in wafer fabs. *International Journal of Production Research, 41*(8), 1765–1784.

Ehteshami, B., Petrakian, R. G., & Shabe, P. M. (1992). Trade-offs in cycle time management: hot lots. *IEEE Transactions on Semiconductor Manufacturing, 5*(2), 101–105.

Fronckowiak, D., Peikert, A., & Nishinohara, K. (1996). Using discrete event simulation to analyze the impact of job priorities on cycle time in semiconductor manufacturing. In *1996 IEEE/SEMI advanced semiconductor manufacturing conference* (pp. 151–155).

Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: Methods and applications, a state-of-the-art survey*. Berlin: Springer-Verlag.

Jaynes, E. T. (1957). Information theory and statistical mechanics. *Physical Review, 106*, 620–630.

Juang, C. H., & Lee, D. H. (1991). A fuzzy scale for measuring weight criteria in hierarchical structures. *International Fuzzy Engineering Symposium*, 415–421.

Kaufmann, A., & Gupta, M. M. (1991). *Introduction to fuzzy arithmetic theory and applications*. New York: Van Nostrand Reinhold.

Klir, G. I., & Yuan, B. (1995). *Fuzzy sets and fuzzy logic theory and applications*. London: Prentice-Hall International.

Kuo, R. J., Chi, S. C., & Kao, S. S. (2002). A decision support system for selecting convenience store location through integration of fuzzy AHP and artificial neural network. *Computers in Industry, 47*, 199–214.

Kwong, C. K., & Bai, H. (2003). Determining the importance weights for the customer requirements in QFD using a fuzzy AHP with an extent analysis approach. *IIE Transactions, 35*, 619–626.

Laarhoeven, P. J. M., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. *Fuzzy Sets and Systems, 11*, 229–241.

Leachman, R. C., & Hodges, D. A. (1996). Benchmarking semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing, 9*(2), 158–169.

Lee, A. H. I., Kang, H. Y., & Wang, W. P. (in press). Analysis of priority mix planning for semiconductor fabrication under uncertainty. *International Journal of Advanced Manufacturing Technology*.

Lee, E. S., & Li, R. L. (1988). Comparison of fuzzy numbers based on the probability measure of fuzzy events. *Computers and Mathematics with Applications, 15*, 887–896.

Liang, G. S., & Wang, M. J. (1994). Personnel selection using fuzzy MCDM algorithm. *European Journal of Operational Research, 78*, 22–33.

Mabuchi, S. (1988). An approach to the comparison of fuzzy subsets with an α-cut dependent index. *IEEE Transactions on Systems, Man, Cybernetics, SMC, 18*(2), 264–272.

Moinpur, R., & Wiley, J. B. (1974). Application of multi-attribute models of attribute in marketing. *Journal of Business Administration, 5*(2), 3–16.

Mon, D. L., Cheng, C. H., & Lu, H. C. (1995). Application of fuzzy distributions on project management. *Fuzzy Sets and Systems, 11*, 229–241.

Murtaza, M. B. (2003). Fuzzy-AHP application to country risk assessment. *American Business Review, 21*(2), 109–116.

Narahari, Y., & Khan, L. M. (1997). Modeling the effect of hot lots in semiconductor manufacturing systems. *IEEE Transactions of Semiconductor Manufacturing, 10*(1), 185–188.

Nijkamp, P. (1997). Stochastic quantitative and qualitative multicriteria analysis for environmental design. *Papers for the Regional Science Association, 39*, 175–199.

SEMI (2002). Provisional guideline for definition and calculation of overall factory efficiency (OFE) and other associated factory-level productivity metrics. SEMI Draft Document 3454.

Shannon, C. E., & Weaver, W. (1947). *The Mathematical Theory of Communication*. Urbana: University of Illinois Press.

Suwignjo, P., Bititci, U. S., & Carrie, A. S. (2000). Quantitative models for performance measurement system. *International Journal of Production Economics, 64*(1–3), 231–242.

Tecnomatix Technologies Ltd (2001). *EM-PLANT objects manual*. Germany: Tecnomatix Software Company.

Uzsoy, R., Lee, C. Y., & Martin-Vega, L. A. (1992). A review of production planning and scheduling models in the semiconductor industry, part I: system characteristics, performance evaluation and production planning. *IIE Transactions on Scheduling Logistics, 24*(4), 47–61.

Yu, C. S. (2002). A GP-AHP method for solving group decision-making fuzzy AHP problems. *Computers and Operations Research, 29*, 1969–2001.

Wei, C. C, Chien, C. F., & Wang, M. J. J. (2005). An AHP-based approach to ERP system selection. *International Journal of Production Economics, 96*(1), 47–62.

Zimmermann, H. J. (1987). *Fuzzy set, decision making and expert system*. Boston: Kluwer.