TECHNOLOGICAL AND ECONOMIC DEVELOPMENT OF ECONOMY
ISSN 2029-4913 / eISSN 2029-4921

2015 Volume 21(2): 301–331
doi:10.3846/20294913.2013.876689

USING A DECISION-MAKING PROCESS TO EVALUATE EFFICIENCY AND OPERATING PERFORMANCE FOR LISTED SEMICONDUCTOR COMPANIES

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Received 19 February 2012; accepted 08 December 2012

Abstract. Today's high-tech industries face increasing competition and challenges. Thus, for high-tech companies, making effective use of resources to enhance business performance and maintain the competitive advantage in the market has become increasingly important. Therefore, this study aimed to design a decision-making model for evaluating the efficiency and operating performance of Taiwan's listed semiconductor companies in 2010 to provide a basis for improving business performance. In view of this, this study combines data envelopment analysis (DEA) and improved grey relational analysis (IGRA) as efficiency tools to measure relative efficiencies; the semiconductor companies are divided into two groups, efficient and inefficient. We then integrate the multiple criteria decision making (MCDM) method (e.g. VlseKriterijumska Optimizacija I Kompromisno Resenje, VIKOR), IGRA and the entropy weight method to evaluate the operating performance of the efficient and inefficient groups, respectively. Establishing a reasonable, objective and valid evaluation model to measure semiconductor companies' operating efficiency can provide company managers, investors and policy makers with a reference for performance evaluation.

Keywords: performance evaluation, efficiency, data envelopment analysis, VIKOR, grey relational analysis, entropy weight.

JEL Classification: G11, G14, L11, L25.

Introduction

Business operators and investors are concerned about how companies view their operating strategies and whether or not they make use of their limited resources. They are also concerned with how the external environment influences the achievement of cost minimization, revenue maximization, and sustainable business performance. Today's high-tech

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industries face increasing competition and challenges. Making effective use of resources to enhance production performance and maintain competitive advantage has become an increasingly important issue. Much of the previous research (Chen *et al.* 2006; Hung, Lu 2008; Wu *et al.* 2007) has paid attention to analyze input-output efficiency and the performance evaluation of the high-tech industries based on DEA. However, in addition to achieving fuller and more efficient use of resources, superior financial performance is the key success factor for companies to remain competitive in high-tech industries. Therefore, this article combines efficiency analysis, production performance and financial performance to construct an effective performance evaluation decision-making process. This approach can provide managers and investors with effective decision making process for performance evaluation.

The concept of efficiency is widely used in the empirical research of company's production performance. From the perspective of resource allocation, efficiency is defined as a minimum input or maximum output with a given set of input. Efficiency measures provide a basis for evaluating and improving company's productivity. They can also help management to understand whether or not the company is achieving effective and efficient resource allocation and use. From the internal point of view of operational efficiency, company performance can be revealed by the efficiency of resource inputs and outputs. In recent years, DEA has been widely used in the analysis of the efficiency of the industry (Cummins *et al.* 2010; Eling, Luhnen 2010; Haugland *et al.* 2007; Staub *et al.* 2010).

In order for a business to achieve sustainable development, it must not only achieve operational efficiency, but it must also have good operational performance. For businesses, excellent operating performance is also a weapon for attracting more investors. In the high-tech industry, decision makers can evaluate the operational performance of a company to understand the efficient use of resources. Meanwhile, with the results of these evaluations, decision-makers can accomplish effective utilization of company resources. Therefore, an effective measure of operating performance will help decision-makers to more effectively manage companies.

In recent years, many studies have used financial indicators to measure performance (Kozmetsky, Yue 1998). M. K. Cetin and E. I. Cetin (2010) mentioned that the financial performance evaluation of companies is a multi-criteria decision making (MCDM) problem. Therefore, MCDM methods have been used in financial performance evaluation, such as in the study by Yalcin *et al.* (2012), who proposed fuzzy MCDM methods for evaluating the Turkish manufacturing industry's financial performance. Wang (2009) combined grey relational analysis (GRA) with a fuzzy multi-criteria group decision-making method to evaluate the financial performance of Taiwan's container lines. Wang and Lee (2010) combined GRA with the fuzzy MCDM method to evaluate financial performance of container shipping companies. However, financial performance indicators do not adequately capture a company's operating results (Tseng *et al.* 2009). Thus, a combination of financial and non-financial indicators to measure operating performance is considered in this study.

Recently, researchers have focused on combining MCDM and other methods in performance evaluation. For example, I. S. Chen and J. K. Chen (2010) used the analytical hierarchy process (AHP), GRA and the technique for order preference by similarity to ideal solution (TOPSIS) to evaluate maintenance performance. Lotfi *et al.* (2011) combined DEA with the TOPSIS method to rank efficient decision-making units (DMUs). Kuo and Liang (2011) combined VIKOR with GRA techniques to evaluate service quality.

Effective utilization of input resources to improve operating efficiency and to increase market competitive ability is a pursuit of each business goal. Because the level of operational efficiency within the industry, the companies competing within the industry are able to achieve different levels of operating performance. Therefore, to provide decision-makers with a clear understanding of the resource usage information enhancing their competitiveness, the proposed method can support the investors fully understand the company's business situation and make the right investment decisions. In order to effectively solve both of the problems mentioned above simultaneously, this study constructs an efficiency analysis and performance evaluation process by combining DEA and IGRA (which we call the DEA-IG model) for efficiency analysis, and then using VIKOR with GRA and the entropy weight method (which we call the VIKOR-IGE model) to evaluate the performance of listed semiconductor companies in Taiwan. An effective measure of business performance will help decision-makers to more effectively manage companies. It could also be used by investors to judge the business growth and development potential based on business performance measurement, thus assisting them in making reasonable and wise investment decisions. The concept of the proposed decision-making process is shown in Figure 1.

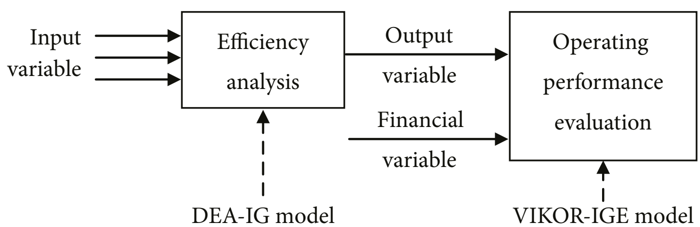

Fig. 1. A conceptual framework of the decision-making process

Many researchers are unable to clearly justify their choice for one MCDM method rather than another (Guitouni, Martel 1998). That is because each method has its own advantages and disadvantages. If we can merge two or more methods into one to overcome the shortcomings of each method, it could increase the credibility of the assessment results. Therefore, the proposed decision-making process in this study was designed in the way that combined the indicator selection method -GRA, efficiency analysis method -DEA, and MCDM method -VIKOR to improve the efficiency of decision-makers, when faced with a large number of evaluation objects. However, there are a variety of existing MCDM methods that we choose to use above decision-making process. Table 1 compares the performance of GRA, DEA, VIKOR and proposed process in terms of weight methods, model characteristics, researcher, method, application area, calculation time and simplicity. Table 1 also shows that each model has its own characteristics and applications. Therefore, a research methodology was applied in this study by using a combination of the characteristics of the various models, the intention is to leverage existing MCDM models to present a novel decision-making process while it applies to the efficiency measurement and performance evaluation that can contribute to the improvement of the decision-making process of both investors and management. However, in practical application, decision makers may not simultaneously have the ability to meet the above-mentioned methods, and then cannot make decisions.

Table 1. Comparison the performance of GRA, DEA, VIKOR and proposed process

MCDM method	Weight method	Model characteristics	Researcher	Method	Application area	Calculation time/ Simplicity
GRA	Equal weight	To deal with the problem of ranking and selection of alternatives	Wang (2008)	GRA + FMCDM	GRA is used to determine representative indicators and FMCDM is used to evaluate the financial performance of airlines.	Moderate/ Moderately
			Kung and Wen (2007)	GRA + GDM	GRA is used to determine representative indicators and GDM is used to arrange the total performance.	Less/ Simple
			Zolfani *et al.* (2012)	FAHP + TOPSIS Grey, SAW-G	FAHP is used to calculate weight. SAW-G and TOPSIS Grey are applied for evaluating alternatives.	High/ Moderately
			Chen (2012)	FAHP + GRA	FAHP is used to calculate weight, and GRA is utilized to rank the Taiwanese automotive industry.	Moderate/ Moderately
DEA	Linear programming	Determine the relative efficiency assessments	Cao and Yang (2011)	Two-stage DEA	Two-stage DEA is used to assess the efficiency of the 40 dot com firms.	Moderate/ Simple
			Wu (2009)	Three-stage DEA + FPR	Three-stage DEA/FPR is developed for performance evaluation.	Moderate/ Moderately
			Wang *et al.* (2010)	Two-stage DEA + GRA	GRA is used to determine representative indicators and two-stage DEA is used to measure production and marketing efficiencies in the printed circuit board industry.	High/ Moderately
			Y. S. Chen and B. Y. Chen (2011)	DEA + MPI	DEA is used to calculate the efficiency of the wafer fabrication industry and MPI is used to evaluate the performance change.	Less/ Simple

Continued Table 1

MCDM method	Weight method	Model characteristics	Researcher	Method	Application area	Calculation time/ Simplicity
VIKOR	Relative weight	Used for ranking the alternatives	Yalcin *et al.* (2012)	FAHP + VIKOR	FAHP is used to calculate weight and VIKOR is used to rank the companies within each sector in the Turkish manufacturing industry.	Moderate/ Moderately
			Sun (2011)	FAHP + VIKOR	FAHP is used to calculate weight and VIKOR is used to rank the notebook computer original design manufacturer companies.	Moderate/ Moderately
			Fu *et al.* (2011)	FAHP + VIKOR	FAHP is used to calculate weight and VIKOR is used to rank the performance of 26 international hotels.	Moderate/ Moderately
			Chou *et al.* (2012)	Entropy + VIKOR	VIKOR and entropy weight method are used to rank the performance of women in the science and technology.	Less/ Simple
			Nayebi *et al.* (2012)	AHP + VIKOR + BSC	AHP is used to calculate weight and VIKOR/BSC is used to rank based on BSC.	Moderate/ Moderately
Proposed process	Entropy weight	Used for ranking the alternatives, relative efficiency assessments and selection of alternatives	None found	GRA + DEA + Entropy + VIKOR	GRA is used to determine representative indicators. DEA is used to assess the relative efficiency. VIKOR and entropy weight method are used to rank the performance of semiconductor companies.	High/ Moderately

FMCDM: fuzzy MCDM, FAHP: fuzzy AHP, GDM: grey decision making, FPR: fuzzy preference relation, MPI: Malmquist productivity index, BSC: Balance Scorecard.

1. Literature review

1.1. The application of GRA

GRA is a correlation analysis method used to analyze the correlation between discrete sequence data (Deng 1988). The main advantages of GRA are that it does not need numerous data, the calculation process is simple and clear, it does not include typical probability distribution, and the conclusion does not conflict with the qualitative analysis (Bindu Madhuri, Anand Chandulal 2010). Therefore, GRA can effectively deal with discrete data. It has been widely applied to different areas such as business, management, engineering and other fields, and has resulted in good results.

GRA had been largely applied to project selection, performance evaluation and selection criteria. For example, Wang (2008, 2009) used GRA to select the representative indicators of financial ratios as evaluation criteria. Wang *et al.* (2010) used GRA to select the representative indicators of 32 efficiency indicators in the printed circuit board industry. Lee *et al.* (2012) proposed combining GRA with the entropy method to rank shipping companies. Sallehuddin and Shamsuddin (2009) used GRA to select appropriate inputs for forecasting. Lin *et al.* (2011) adopted GRA to determine the key success factors of the purchasing decision-making of overseas importers of Taiwanese products and Taiwanese exporters. From the above literature review, it is evident that the application of GRA for selecting representative indicators is appropriate. Therefore, in this study, GRA is used to select tools for extracting the representative factors which describe the system.

1.2. The application of entropy method

After Shannon and Weaver used entropy in the information theory in 1949 (Shannon, Weaver 1949), the entropy method has received rapid development and wide application. There are numerous different methods to determine the attribute weight. The entropy weight method is one such weight method. It uses the entropy value to define the weight of each indicator, so it is an objective weight method. The advantage of the entropy weight method is that it calculates the weight to avoid the influence of subjective factors based on objective data. However, it does not reflect the decision-makers' attribute preference. The entropy method is now widely used in MCDM problems as a method to measure the weights of attributes. For example, Wu and Liu (2011) proposed a VIKOR algorithm with the entropy method to deal with supplier selection problems. Shemshadi *et al.* (2011) proposed a fuzzy VIKOR method with the entropy method to deal with supplier selection problems. Yan *et al.* (2011) established an entropy-TOPSIS model to evaluate the impact of the external environment. Han and Liu (2011) proposed a TOPSIS combined with the entropy weight method to solve a hybrid multiple attribute decision-making problem. From the above literature review, it is evident that using entropy weight to deal with MCDM problems is appropriate. Therefore, this study adopts the entropy weight method to determine the attribute weights.

1.3. The application of DEA in the high-tech industry

As for the relationship between the inputs and outputs, the efficiency can be considered as the performance of processes that transform a set of inputs into output. Coelli *et al.* (1998) mentioned that the two most common ways to measure efficiency are the parametric approach and non-parametric approach. The main disadvantage of the parametric approach is the particular functional form requirement and the assumption of the distribution of the error term. In contrast, the non-parametric approach using a mathematical programming technique does not require a particular functional for the frontier, making it more flexible in its application.

The most common non-parametric approach is data envelopment analysis (DEA), which was introduced by Charnes *et al.* (1978). Since Charnes *et al.* (1978) proposed the DEA method for the evaluation of relative efficiency, it has been widely used to explore and analyze the efficiency of organizations. Avkiran (2001) pointed out that DEA is an effective and good tool for measuring efficiency. Therefore, DEA is widely used in the calculation of the relative efficiency of DMUs and as a performance measurement technique. It has both advantages and disadvantages. The main advantage of DEA is that it does not require the specification of a particular functional form; the weights of the decision were not influenced by subjective factors, and handle multiple inputs and outputs for calculating efficiency. However, the disadvantage of DEA is that it cannot deal with negative input or output values; thus one needs to select the input and output variables very carefully in practical applications.

In recent years, numerous scholars have used DEA for the benefit of industry, and to analyze the operating efficiency of high-tech companies. In the high-tech industry, the semiconductor industry is based on knowledge, technology and capital-intensive business. It is also a global industry. Therefore, many researchers have used the DEA method to evaluate the operating efficiency of the high-tech industry. For example, Chen *et al.* (2006) applied DEA to evaluate the relative efficiencies of six high-tech companies in Taiwan. Liu and Wang (2008) used DEA to measure the Malmquist productivity of semiconductor packaging and testing firms in Taiwan. Pan *et al.* (2008) adopted DEA models to examine the performance of the 72 integrated circuit design industry. T. Y. Chen and L. Chen (2007) used DEA to evaluate the performance of the semiconductor industry in Taiwan. Lu and Hung (2010) used DEA to evaluate the performance of the 48 semiconductor companies in Taiwan. Lu (2011) adopted DEA to evaluate the production efficiency of Taiwan's integrated circuit (IC) subsectors. Hung and Liu (2010) used DEA to analyze the influence of perfluorocompounds (PFCs) on the operating performance of the semiconductor industry.

DEA is based on the concept of relative efficiency. DEA can be used to measure the relative operational efficiency of decision making units and it can effectively process multiple inputs and multiple outputs models. Moreover, researches have confirmed that DEA appropriates evaluating the efficiency of the semiconductor industry. Therefore, this study combined DEA and IGRA (DEA-IG model) to evaluate the operating efficiency of the semiconductor industry in Taiwan.

1.4. The application of the VIKOR method for performance evaluation

MCDM is an appropriate tool for analyzing decision problems when facing multiple conflicting criteria. It can help the decision maker to make more accurate decisions, and it is often used in the evaluation and selection of the object. There are many types of MCDM methods which have been widely used in various fields, such as business and financial management, transportation and logistics, manufacturing and assembly, managerial and strategic planning, project management and evaluation, and so on (Toloie-Eshlaghy, Homayonfar 2011). This study focused on the application of MCDM to evaluate and rank the performance of semiconductor companies. However, selecting a feasible and effective method for evaluation of performance is not an easy task.

Numerous MCDM methods have been used in the past. Different MCDM techniques suit different kinds of decision analysis situations. Zavadskas and Turskis (2011) gave a good review and classification of the MCDM approach in economics. They classified the MCDM methods into eleven categories, i.e. the AHP (Hadi-Vencheh, Mohamadghasemi 2011), the utility additive method (UTA) (Athawale *et al.* 2011), complex proportional assessment (COPRAS)

(Podvezko 2011), TOPSIS (Han, Liu 2011), VIKOR (Ginevičius *et al.* 2010), the additive ratio assessment method (ARAS) (Bakshi, Sarkar 2011), simple average weight (SAW) (Podvezko 2011), elimination and choice translating reality (ELECTRE) (Kaya, Kahraman 2011), the preference ranking organization method for enrichment evaluation (PROMETHEE) (Ishizaka, Nemery 2011), multi-objective optimization by ratio analysis (MOORA) (Baležentis, Baležentis 2011) and the game theory (Stein 2010).

Among the MCDM methods, TOPSIS and VIKOR to deal with the competitive nature of all criteria ranking on the basis of the concept of compromise (Opricovic, Tzeng 2004). Some previous studies have compared these two models. For example, Opricovic and Tzeng (2004) compared TOPSIS and VIKOR, showing their similarity and some differences. Chu *et al.* (2007) compared three MCDM methods, SAW, TOPSIS and VIKOR, showing that both the TOPSIS and VIKOR methods are suitable for evaluating similar problems, but VIKOR is easy for choice appropriate strategies. Liu and Wang (2011) also mentioned that VIKOR is generally suitable for decision making problems.

Therefore, the VIKOR method has been used by researchers to solve decision making problems. For example, Lu and Tang (2011) used the VIKOR method for evaluating auto parts suppliers. Kuo and Liang (2011) combined VIKOR and interval-valued fuzzy sets to evaluate the performance of intercity bus companies. Tsai *et al.* (2010) used the VIKOR method to rank Taiwanese national park websites. F. L. Chen and Y. C. Chen (2010) used the VIKOR method to rank life insurance companies in Taiwan. Shaverdi *et al.* (2011) used the TOPSIS, VIKOR, and ELECTRE methods to rank banking performance. From the above literature review, it is evident that VIKOR is commonly used in evaluation. Thus, this study aimed to combine VIKOR with IGRA and the entropy weight method (VIKOR-IGE model) to evaluate and rank the performance of semiconductor companies.

2. Methodology

2.1. IGRA

GRA was used to analyze the relationship between two series. It can deal effectively with multi-variable input, less data and data distribution unknown to overcome the disadvantages of traditional statistical methods. Today, GRA is widely and commonly used as a method for selecting representative indicators, such as Ho (2006), Hsu (2014), Huang and Wan (2011), Kung and Wen (2007), Lee *et al.* (2012) and Li (2011). Therefore, this study applies IGRA as an indicator selection method for (1) selecting input and output variables to use in the DEA model, (2) selecting representative indicators of financial ratios for evaluating performance.

Before conducting GRA, in order to achieve comparability between sequences, the data series must be normalized. There are three different types of data normalization, including the larger the better, the smaller the better, and the nominal the better. Details are shown as follows:

(1) the larger the better

$$\gamma_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, \tag{1}$$

(2) the smaller the better

$$\gamma_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, \tag{2}$$

(3) the more nominal the better

$$\gamma_{ij} = \frac{\left| x_{ij} - x_{obj} \right|}{\max_i x_{ij} - x_{obj}}, \tag{3}$$

where $\max_i x_{ij} \geq x_{ij} \geq \min_i x_{ij}$, x_{obj} is the desired value of the *j*th quality characteristic.

GRA includes localized and globalized grey relational grades. If the conductor chooses an arbitrary sequence as a reference sequence and other sequences are compared to the sequence, it is called localized GRA. If each sequence can be the reference sequence, then, it is called globalized GRA. This study used the globalized GRA method. However, traditional GRA is not a perfect method. The disadvantage of traditional GRA is that the value of grey relational grade between the alternative and the ideal alternative is too close. It results that it does not clearly identify the correlation between the two sequences. This study proposed the globalized IGRA method modify traditional GRA based on the improved grey relational grade. The steps of the globalized IGRA method are described as follows:

Step 1. Calculate the grey relational coefficient: Wong and Lai (2000) proposed a grey relational coefficient to improve the Deng's grey relational coefficient calculation, as follows:

$$\gamma\left(x_i(k), x_j(k)\right) = \left\{ \frac{\Delta_{\max} - \Delta_{ij}(k)}{\Delta_{\max} - \Delta_{\min}} \right\}^{\zeta}, \tag{4}$$

where $k = 1,2,\cdots,n$, $i = 1,2,\cdots,m$, $j \in i$, $\Delta_{ij}(k) = \left| x_i(k) - x_j(k) \right|$ is the absolute value of difference between $x_i(k)$ and $x_j(k)$. $\Delta_{\max} = \max_i \max_j \max_k \left| x_i(k) - x_j(k) \right|$ and $\Delta_{\min} = \min_i \min_j \min_k \left| x_i(k) - x_j(k) \right|$ are the maximum and the minimum value of $\Delta_{ij}(k)$, respectively, and ς is the distinguishing coefficient, $\varsigma \in [0,1]$. In general, it is set to 0.5 (Wen 2004).

In this study, we consider the distance between the evaluation object and the optimal solution; we use the adjustment coefficient η to adjust the proportion of the sort and to construct the grey relational coefficient as follows:

$$\gamma'\left(x_i(k), x_j(k)\right) = \eta \left\{ \frac{\Delta_{\max} - \Delta_{ij}(k)}{\Delta_{\max} - \Delta_{\min}} \right\}^{\zeta} + (1-\eta)\left[1 - \frac{\Delta_{ij}(k)}{\Delta_{\max}} \right], \tag{5}$$

where $k = 1,2,\cdots,n$, $i = 1,2,\cdots,m$, $j \in i$, $1 - \frac{\Delta_{ij}(k)}{\Delta_{\max}}$ is the distance term, adjustment coefficient η was set as 0.5, which is the same value used in distinguishing coefficient.

Step 2. Calculate the grey relational grade: The grey relational grade is obtained from the average of the grey relational coefficient, as follows:

$$\Gamma_{ij} = \Gamma(x_i, x_j) = \frac{1}{n}\sum_{k=1}^{n} \gamma'\left(x_i(k), x_j(k)\right), \tag{6}$$

where Γ_{ij} indicates the magnitude of correlation measured between the reference sequences (x_i) and the comparison sequence (x_j).

Step 3. Construct the grey relational coefficient matrix: A grey relational coefficient matrix is composed of each grey relational grade from Eq. (6), that is:

$$M_{m\times m} = \begin{bmatrix} \Gamma_{11} & \Gamma_{12} & \cdots & \Gamma_{1m} \\ \Gamma_{21} & \Gamma_{22} & \cdots & \Gamma_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \Gamma_{m1} & \Gamma_{m2} & \cdots & \Gamma_{mm} \end{bmatrix}_{m\times m}. \tag{7}$$

Step 4. According to the equation $\det\left(M - \lambda I\right) = 0$, find the maximum eigenvalue $\lambda_{\max}$.

Step 5. Choose the eigenvector corresponding to the largest value $\lambda_{\max}$ and rank the grey relational ordinal according to the result.

2.2. Entropy weight method

Shannon (1948) proposed the concept of entropy, which is a measure of information and uncertainty. In recent years, entropy has been applied to measure attribute weights (Han, Liu 2011; Lee *et al.* 2012; Shemshadi *et al.* 2011; Wu, Liu 2011; Yan *et al.* 2011). As mentioned in Section 1.2, the entropy weight method has the advantage to solve the weight calculation problem. Therefore, this study adopts the entropy weight method to calculate the weight value. The steps are shown as follows:

Step 1. Normalize the original evaluation matrix: There are many methods for data normalization. Chiang and Hsieh (2009) proposed Eqs (1)–(3) for data normalization, obtaining the following matrix:

$$F = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1n} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{m1} & \gamma_{m2} & \cdots & \gamma_{mn} \end{bmatrix}_{m\times n}, \tag{8}$$

where γ_{ij} is the data of the *i*th evaluating object on the *j*th indicator, and $\gamma_{ij} \in [0,1]$.

Step 2. Calculate the entropy value of evaluation indicator *j*: According to Wen (2004), the entropy value of the *j*th is defined as follows:

$$e_j = \frac{1}{0.6487m}\sum_{i=1}^{m} We\left(\frac{\gamma_{ij}}{D_j}\right), \tag{9}$$

where: $j = 1,2,\ldots,n,\ W_e = x e^{(1-x)} + (1-x)e^x - 1,\ D_j = \sum_{i=1}^{m}\gamma_{ij}$.

Step 3. Determine the weight of the evaluation criteria w_j: According to Wen (2004), the weight of the evaluation component is as follows:

$$w_j = \frac{\frac{1}{n-E}\left[1-e_j\right]}{\sum_{j=1}^{n}\frac{1}{n-E}\left[1-e_j\right]},\ j=1,2,\ldots,n, \tag{10}$$

where: $E=\sum_{j=1}^{n} e_j$.

2.3. DEA-IG model

DEA is a mathematical method for measuring the relative efficiencies of DMUs based on multiple inputs and outputs. It is used to distinguish between efficient and inefficient DMUs. Farrell (1957) developed a method using the production frontier approach to measure technical efficiency and price efficiency, in order to establish a mathematical programming model to measure efficiency. Later, Charnes *et al.* (1978) measured the efficiency value under multiple inputs and outputs with the assumption of constant return to scale. Their approach is called data envelopment analysis (CRS or the CCR model). Subsequently, Banker *et al.* (1984) proposed a model to relax the assumption of CRS by introducing the variable returns to scale (VRS) (known as the BCC model), making the DEA model more generous. According to Cooper *et al.* (2000), there are two types of efficiency measure in DEA, radial and non-radial measure. The above-mentioned CCR and BCC models are based on the radial measure. As for the non-radial measure, Tone (2001) proposed a slack-based measure (SBM), which based on the slack variables, is used to overcome the weakness in the CCR and BCC models. It shows that the SBM model has higher discrimination power than that of radial measure models. Therefore, this study used the SBM, CCR and BCC models to analyze the efficiency of semiconductor companies.

The mathematical expressions of the DEA models are as follows:

(1) CCR model

The CCR model assumes that the frontier is constant returns to scale, as proposed by Charnes *et al.* (1978). Suppose there are *n* DMUs ($j=1,\cdots,n$), with *m* input X_i ($i=1,\cdots,m$) to generate s outputs Y_r ($r=1,\cdots,s$). Then, the efficiency values of DMU_0 (h_i) are as follows:

$$Max \quad h_i = \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}}; \tag{11}$$

$$s.t. \quad \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \le 1,$$

where: $u_r, v_i \ge \varepsilon > 0$, $j=1,\cdots,n$, $i=1,\cdots,m$, $r=1,\cdots,s$. X_{ij}, Y_{rj} are *i*th input and *r*th output of *j*th DMU; u_r and v_i are the weights of the input and output; ε is a very small positive number, usually set to 10^{-6}, where there is a small non-Archimedean number (Charnes, Cooper 1984).

(2) BCC model

Banker *et al.* (1984) improved the CCR model and proposed the BCC model by assuming that VRS can measure both the pure technical efficiency (PTE) and scale efficiency (SE) as a way to explain the cause for the formation of weak efficiency in the CCR model. Therefore, the BCC model is a measure of pure technical efficiency. The CCR model measures the technical efficiency (TE), and the difference is the scale efficiency, where SE=TE/PTE. Two commonly used DEA orientation models are the input-oriented and output-oriented models of BCC. The input-oriented model measures how many fewer input resources can maintain the same level of outputs. The output-oriented model uses the same input level to yield more output.

The semiconductor industry involves build-to-order (BTO) operation, which requires meeting market demands for changes in input resources. Therefore, in this study, we chose the input oriented model. The analytical model is as follows:

$$Max \quad g_j = \sum_{i=1}^{s} u_r Y_{rj} - u_0 ; \tag{12}$$

$$s.t. \quad \sum_{i=1}^{m} v_i X_{ij} = 1;$$

$$\sum_{i=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 ,$$

where: $u_r, v_i \geq \varepsilon > 0;\ j = 1,\cdots,n;\ i = 1,\cdots,m;\ r = 1,\cdots,s.$

(3) SBM model

The SBM was first proposed by Tone (2001), which was non-radial and took into account the input and output slacks. It has the following three features: unit invariant, monotonicity, and efficiency index value only by the efficiency reference set. Suppose there are n DUMs, with m input factors and s output factors. Let x_{ij} and y_{ij} denote the ith input and output of DMU j. The input-oriented SBM model evaluates the technical efficiency τ^* of DMU (x_o, y_o) is as follows (Cooper *et al.* 2006; Tone, Tsutsui 2010):

$$\underset{\lambda, s^-}{Min} \ \tau^* = 1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{io}} ; \tag{13}$$

$$s.t. \quad x_{io} = \sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- ;$$

$$y_{io} < \sum_{j=1}^{n} y_{ij} \lambda_j ;$$

$$\lambda_j \geq 0 ,\ s_i^- \geq 0 , i = 1,2,\cdots,m ,$$

where: τ^* is the SBM of technical efficiency value; λ_j is the weight of DMU j; s^- is the non-radial input slacks. It can be obviously identified that $0 < \tau^* \leq 1$. A DMU is efficient when $\tau^* = 1$ and it is inefficient if $\tau^* < 1$.

Therefore, we propose the DEA-IG model to evaluate the relative efficiency of the semiconductor companies. First, we use globalized IGRA to select representative indicators for input and output variables. Then, we apply a DEA model using the CCR, BCC and SBM methods to assess the relative efficiency of these companies. The steps as follows:

Step 1. Use globalized IGRA to select representative indicators for input and output variables: First, for data normalization, since the smaller the input the better, we adopt Eq. (2) to normalize input data. However, the larger the output is the better, so we adopt Eq. (1) to normalize output data. Then, following the steps given in Section 2.1 (Steps 1–5), we can obtain the input and output of the grey relational ordinal, respectively. Finally, select the larger grey relational grade of the input and output variables as representative indicators for DEA.

Step 2. Using the selected input and output variables to solve the problem with the CCR model (Eq. (11)) and SBM model (Eq. (13)); we can obtain the aggregate TE of each DMU. Then, we use the BCC model to analyze the PTE and SE of each DMU. For efficient DMUs, the efficiency scores are equal to one, and inefficient DMUs have efficiency scores less than one. The results from the DEA model of the semiconductor industry companies can be divided into groups of efficient DMUs and inefficient DMUs.

2.4. VIKOR-IGE model

There are numerous multiple criteria decision making (MCDM) methods (Guitouni, Martel 1998). Among which, the VIKOR and TOPSIS methods are based on the concept of compromise solutions (Opricovic, Tzeng 2004). It is known that the TOPSIS method can not correctly reflect the distance from each object to positive-ideal solution and negative-ideal solution (Opricovic, Tzeng 2004). Olson (2004) mentioned TOPSIS method using the m-dimensional Euclidean distance to calculate the separation measure is not appropriate. VIKOR has advantages which can determine a compromise solution to reflect the attitude of most decision-makers for the decision-making problem. Therefore, this study applied the VIKOR method (Azimi *et al.* 2011; Chang, Hsu 2009; Opricovic 1998; Opricovic, Tzeng 2004, 2007) to improve its shortcomings and increase the validity of the model.

However, the disadvantage of traditional VIKOR is that selecting the evaluation criteria and the weight of the decision has a significant influence on the results of evaluation. Therefore, in this study a combined VIKOR method based on globalized IGRA and entropy weight was proposed for improving the above-mentioned disadvantages. Globalized IGRA (Section 2.1) is used to select the representative indicators for evaluating performance, and the entropy weight is used to obtain the weights of all evaluation criteria in the VIKOR method. Thus, the proposed VIKOR-IGE model can be summarized as follows:

Step 1. Selecting representative performance indicators to use in the VIKOR based on the entropy weight model: In this study, we first calculate the grey relational grades between the performance indicators (Eqs (5)–(7)). According to the value of grey relational grade, we can partition performance indicators into several groups by threshold value. Then, choose one from each group as a representative indicator.

Step 2. Construct the normalized decision matrix: The results from the DEA model indicate groups of efficient and inefficient companies respectively. Then, according to the selected representative indicators, we obtain the normalized decision matrix after normalization by Eqs (1)–(3),

$$F = \left[\gamma_{ij}\right]_{m\times n}, i=1,2,\ldots,m, \; j=1,2,\ldots,n, \tag{14}$$

where γ_{ij} denotes the performance evaluation value of the ith evaluating object on the jth indicator, the same as in Eq. (8).

Step 3. Determine the positive ideal solution (f^*) and the negative ideal solution (f^-) for all evaluation criteria. Then the ideal solution set f^* and f^- can be expressed as:

$$f_i^* = [(\max{}_j \gamma_{ij} \left| i \in I_1\right.) , (\min{}_j \gamma_{ij} \left| i \in I_2\right.)] , \forall_i; \tag{15}$$

$$f_i^- = [(\min{}_j \gamma_{ij} \left| i \in I_1\right.) , (\max{}_j \gamma_{ij} \left| i \in I_2\right.)] , \forall_i , \tag{16}$$

where I_1 is associated with benefit criteria, and I_2 is related to the cost criteria.

Step 4. Calculate the criteria weights using the entropy weight method: There are a lot of methods for calculating the weight. In order to avoid the influence of subjective factors of the decision-maker, this study uses the entropy weight method to find the weight of each criterion. We use the normalized decision matrix F to calculate the entropy weight of each evaluation criterion by using Eqs (8)–(10).

Step 5. Calculate the utility measure and regret measure: The utility measure (S_j) and the regret measure (R_j) for each jth indicator are given as:

$$S_j = \sum_{i=1}^{n} w_i (f_i^* - f_{ij}) / (f_i^* - f_i^-); \tag{17}$$

$$R_j = \max_i \left[w_i (f_i^* - f_{ij}) / (f_i^* - f_i^-) \right], \; j = 1,2,\ldots J. \tag{18}$$

Step 6. Calculate the VIKOR index Q: The VIKOR index of the jth evaluating object can be expressed as:

$$Q_j = v\left[\frac{S_j - S^*}{S^- - S^*}\right] + (1-v)\left[\frac{R_j - R^*}{R^- - R^*}\right], \tag{19}$$

where: $S^* = \min_j S_j$, $S^- = \max_j S_j$, $R^* = \min_j R_j$, $R^- = \max_j R_j$. The v is the coefficient for the decision-making mechanism, and is usually taken as 0.5 (Purjavad, Shirouyehzad 2011).

Step 7. VIKOR index ranking: The evaluation objects are ranked according to the values of Q_j, S_j, and R_j. When the following two conditions are satisfied, then we can rank the evaluation objects (Q_j is the smaller the better) according to the value of Q_j.

Condition 1. Acceptable advantage: The threshold condition for acceptable advantage is:

$$Q'' - Q' \geq 1/(J-1), \tag{20}$$

where Q' denotes the Q value that is ranked first, Q'' denotes the Q value that is ranked second, and J is the number of evaluation objects.

Condition 2. Acceptable stability in decision-making: According to the rank of Q, the first ranked $S\ (R)$ value must be higher than the second ranked $S\ (R)$ value.

If one of the above conditions is not satisfied, then we can get the compromised solution by following the judge rules. That is, when the first and second ranked objects satisfy both condition 1 and condition 2, then the first ranked object is the best object. If the first and second ranked objects only fail to satisfy condition 2, then the first and second ranked objects are the best objects simultaneously. When condition 1 is not satisfied, then objective M is determined by $Q^M - Q' \geq 1/(J-1)$ as the maximum M. At this point, objective 1 to M shall be taken as the compromised solutions, which are the best objects simultaneously.

3. Empirical results

3.1. Efficiency analysis with the DEA-IG model

In order to measure the operating efficiency of DMUs, this study proposes a DEA-IG model combined IGRA and DEA as described below.

3.1.1. Determining DMUs and data source

Using DEA for efficiency analysis, when selecting a different member of DMUs, input and output variables will yield different efficiency values. Therefore, the DMUs selected must be homogeneous and under the same market condition to avoid distortion of the assessment results. In addition, when selecting the number of DMUs, Golany and Roll (1989) established a rule of thumb that the number of the assessed units should be at least twice the sum of the number of input and output variables.

Semiconductors have played an important role in today's high-tech industry, and after the twenty-first century, the semiconductor industry is widely regarded as an important investment (Hung, Lu 2008). The output value of Taiwan's semiconductor industry has reached approximately 20% of the global semiconductor industry, giving Taiwan a very important position in the global market. In Taiwan, the semiconductor industry is a direction of future high-technology investment development and also the major recipient of investment projects. Therefore, this study takes listed semiconductor companies in Taiwan as a case to verify the developed decision-making process.

Within DEA procedure, we first need to determine the DMUs. This study chooses the listed companies in the Taiwan's semiconductor industry (including integrated circuit (IC) design, manufacturing, packaging, and testing companies) as a sample. Companies with missing or incomplete data were excluded. The total number of listed semiconductor companies used in this study is 38, and we include 14 IC design companies (36, 8%), 11 IC fabrication companies (29.0%), 13 IC packaging and testing companies (34.2%), which are taken as DMUs. The input and output variables and financial data of Taiwan's semiconductor companies in 2010 were collected from the Taiwan Economic Journal (TEJ) database.

3.1.2. Selection of input and output variables

The selection of input and output variables is the most important issue for the application of DEA (Morita, Avkiran 2009). According to the recommendation of Golany and Roll (1989), this study followed past research and stayed within the characteristics of the semiconductor industry to select the input and output variables. The input variables include the following: (1) R&D expenses (Chang *et al.* 2011; Ho *et al.* 2011); (2) Administrative expenses (Chang *et al.* 2011; Zou, Huan 2011); (3) Fixed assets (Zou, Huan 2011); (4) Selling expenses (Ho *et al.* 2011); (5) Number of employees (Chang *et al.* 2011; Zou, Huan 2011); (6) Inventory (Lee, Park 2005); (7) Operating expenses (Eken, Kale 2011; Ho *et al.* 2011); (8) Total debt (Diskaya *et al.* 2011); and (9) Total assets (Duran, Zehir 2011; Halkos, Tzeremes 2012; Ho *et al.* 2011).

Moreover, the output variables include the total revenue (Chiu, Huang 2011; Shuai, Wu 2011), net sales (Duran, Zehir 2011; Tsai 2011; Wang *et al.* 2011), net profit ratio (Lee, Pai 2011), operating income (Long, Li 2011; Wang *et al.* 2011) and gross profit margin (Duran, Zehir 2011).

3.1.3. The result of the DEA-IG model

In this study, the CCR, BCC and SBM models were used to evaluate the technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) of the listed semiconductor companies in Taiwan in 2010. The DEA software DEAP 2.1 (Coelli 1996) and DEA Excel Solver (Zhu 2003) were used to calculate a company's relative efficiency. The results of efficiency analysis can indicate whether a company is relatively efficient or inefficient.

First, we need to select the representative indicators from nine input and five output variables (Table 2), respectively. We also need to ensure that DEA efficiency analysis can effectively show the listed semiconductor company's operating performance. Therefore, this study uses the globalized IGRA method (Section 2.1) to calculate the maximum eigenvalue λ_{max} of input and output variables as 8.461 and 4.367, respectively. Then we can calculate the eigenvector for each variable. The results are shown in Table 2. In this study, variables with eigenvectors greater than 0.335 and 0.47 were used to form the representative input and output variables, respectively. The selected input variables include total assets, operating expenses, administrative expenses, inventory, and the selected output variables are total revenue and net sales.

Table 2. The selection of input and output variables based on the globalized GRA

Input			Output		
Variable	Eigenvector	Selected	Variable	Eigenvector	Selected
Number of employees	0.331		Total revenue	0.470	*
Fixed assets	0.334		Net sales	0.471	*
Total asset	0.338	*	Net profit ratio	0.466	
Total debt	0.328		Gross profit margin	0.349	
Operating expenses	0.338	*	Operating income	0.467	
Selling expenses	0.329				
Administrative expenses	0.337	*			
R&D expenses	0.329				
Inventory	0.335	*			

Then, the selected four inputs and two outputs were used in the DEA efficiency analysis of 38 listed semiconductor companies in Taiwan. When using DEA to evaluate operating efficiency, the input and output variables should confirm to isotonicity (i.e. the input and output variables are all positively correlated) (Avkiran 1999). That is, when higher levels of input lead to higher levels of output, the operating efficiency factor should be positive. Table 3 shows the Spearman correlation coefficients between input and output variables. The results indicate that a statistically significant positive correlation was obtained, and the isotonicity test was passed.

Table 3. Spearman's correlation coefficients between input and output variables

	1	2	3	4	5
1. Total revenue					
2. Net sales	0.995**				
3. Total asset	0.933**	0.910**			
4. Operating expenses	0.830**	0.797**	0.942**		
5. Administrative expenses	0.917**	0.902**	0.936**	0.950**	
6. Inventory	0.798**	0.770**	0.906**	0.977**	0.951**

**: $p < 0.01$

Standard DEA can be modeled in two ways, input oriented (control for the input variables), and output oriented (control for the output variables) DEA models (Ray 2004). From the business point of view of a company, it is easy to reduce input rather than increase output. Thus, this study used the input oriented DEA model to obtain the relative operational efficiency of the semiconductor companies. The CCR, BCC and SBM models are used to evaluate the relative operational efficiency of 38 Taiwan semiconductor companies in 2010.

The three calculated efficiency scores (TE, PTE and SE) are given in Table 4. The TE scores can be obtained from the input oriented CCR model (Charnes *et al.* 1978) and input oriented SBM model (Tone 2001). The PTE score can be obtained from the input oriented BCC model (Banker *et al.* 1984), and SE can be computed by SE=TE/PTE. A TE score equal to one implies full efficiency. In contrast, if the score is less than one, it indicates technical inefficiency. If the PTE score of a company is equal to one, then the company is considered as efficient. If the value of PTE is less than one, then the company is operating under pure technical inefficiency. When the value of SE is equal to one, it implies the company is operating under constant return to scale (CRS). If the SE is less than one, the company is scaled as inefficient; it will be under increasing return to scale (IRS) or decreasing return to scale (DRS). Therefore, efficient companies (DMUs) are identified by an efficiency score equal to 1. Table 4 shows that only 11 companies were relatively efficient and the remaining 27 were inefficient, i.e. their TE and PTE scores were below 1. The average values of TE obtained from the CCR and SBM were 0.850 and 0.743, respectively; PTE and SE were found to be 0.797, 0.86 and 0.925, respectively. Table 4 also provides the returns to scale information of each inefficient company. We find that 8 companies show IRS, and 18 companies show DRS.

Table 4. Efficiency values of companies based on CCR and BCC models

DMU (Company)	CCR (TE)	BCC (PTE)	Scale (SE)	SBM (TE)	Returns to scale
F1	0.650	0.720	0.903	0.431	DRS
F2	1.000	1.000	1.000	1.000	CRS
F3	0.605	0.764	0.791	0.475	DRS
F4	0.786	0.799	0.984	0.661	DRS
F5	0.843	1.000	0.843	0.752	IRS
F6	1.000	1.000	1.000	1.000	CRS
F7	0.851	0.879	0.968	0.664	DRS
F8	1.000	1.000	1.000	1.000	CRS
F9	0.715	0.764	0.937	0.547	DRS
F10	1.000	1.000	1.000	1.000	CRS
F11	0.898	0.963	0.933	0.706	DRS
F12	0.766	1.000	0.766	0.611	DRS
F13	0.863	0.865	0.999	0.636	IRS
F14	1.000	1.000	1.000	1.000	CRS
F15	0.832	0.914	0.910	0.675	DRS
F16	1.000	1.000	1.000	1.000	CRS
F17	0.671	1.000	0.671	0.505	DRS
F18	0.686	0.687	0.999	0.624	IRS
F19	0.837	0.844	0.992	0.701	DRS
F20	0.984	1.000	0.984	0.660	DRS
F21	0.634	0.663	0.956	0.562	IRS
F22	1.000	1.000	1.000	1.000	CRS
F23	0.734	0.742	0.989	0.623	DRS
F24	0.999	0.999	1.000	0.864	DRS
F25	0.710	0.714	0.995	0.650	DRS
F26	0.857	1.000	0.857	0.698	DRS
F27	0.994	1.000	0.994	0.942	DRS
F28	0.772	0.776	0.994	0.724	IRS
F29	1.000	1.000	1.000	1.000	CRS
F30	0.845	0.859	0.983	0.737	IRS
F31	0.686	0.937	0.732	0.595	DRS
F32	0.707	0.804	0.880	0.536	IRS
F33	1.000	1.000	1.000	1.000	CRS
F34	1.000	1.000	1.000	0.750	CRS
F35	0.654	1.000	0.654	0.389	IRS
F36	1.000	1.000	1.000	1.000	CRS
F37	0.727	1.000	0.727	0.500	DRS
F38	1.000	1.000	1.000	1.000	CRS
Mean	0.850	0.913	0.933	0.743	

CCR: constant returns to scale (total technical efficiency, TE), BCC: variable returns to scale (pure technical efficiency, PTE), scale: scale efficiency (SE), SBM: slack-based measure, DRS: decreasing return to scale, CRS: constant return to scale, IRS: increasing return to scale.

3.2. The results of performance evaluation with the VIKOR-IGE model

For performance evaluation, this study proposed a VIKOR-IGE model which combines globalized IGRA, the entropy weight method and the VIKOR method to evaluate the performance of 38 listed semiconductor companies in Taiwan (F1 to F38), as described below.

3.2.1. Using GRA to select the representative indicators for performance evaluation

In this study, two types of indicators concerning performance are applied to evaluate the companies. Both financial and non-financial performance indicators are used to evaluate company's performance. We use the selected output variables in Section 2.1.2, total revenue and net sales, as non-financial performance criteria. Three types of financial categories, profitability, solvency and operating ability are used to measure financial performance. 17 financial indicators were selected, as defined in Table 5. As listed in Table 5, the most critical of the

Table 5. The financial indicators on three categories

Category	Code	Financial ratios	Definition	Target
Profitability	P1	Returns on assets (ROA)	[Earning + interest expenses × (1-tax rate)]/ Average total assets	Max
	P2	Returns on equity (ROE)	Current term net profit/Shareholder equity	Max
	P3	Operating profit margin	Operating profit/Operating revenue	Max
	P4	Net profit margin after tax	Net profit after tax/Operating revenue	Max
	P5	Earnings per share	Total profits of a company/ Number of shares	Max
Operating ability	O1	Total assets turnover	Net operating revenue/Total assets	Max
	O2	Accounts receivable turnover	Net sales/Average balance of account receivable	Max
	O3	Inventory turnover	Cost of sales/Average inventory	Max
	O4	Average daily sales	365/Inventory turnover	Min
	O5	Fixed assets turnover	Net operating revenue/Total fixed assets	Max
	O6	Shareholder equity turnover	Operating revenue/Shareholder equity	Max
Solvency	S1	Current ratio	Current assets/Current liabilities	Max
	S2	Quick ratio	(Current assets – Inventories)/ Current liabilities	Max
	S3	Debt ratio	Total debt/Total assets	Min
	S4	Long-term capital ratio	(Net shareholder's equity + Long-term liabilities)/Net fixed assets	Max
	S5	Cash flow ratio	Net cash provided by operating activities/ Current liabilities	Max
	S6	Cash reinvestment ratio	(Net cash flow from operating activities-cash dividend)/(Total fixed assets + Long-term investments + Other assets + Working capital)	Max

financial indicators are the larger the better (Target: Max), but some are the smaller the better (Target: Min). Financial indicators have different attributes. Wang (2008, 2009) mentioned that the use of representative financial indicators to evaluate the financial performance of a company is a MCDM problem, and selecting the representative financial indicators plays a very important role in the performance evaluation of companies.

This study based on the work of Feng and Wang (2000) and Wang (2008, 2009) who proposed a method to select the representative financial indicators. That is, first using the globalized IGRA to cluster financial indicators from three categories into several groups. Then, calculate the total score according to the ranking results. The total score which is the highest is selected as the representative financial indicator of the group.

First, according to the data type of the 17 financial indicators in Table 5, the larger the better (i.e. target is max) and the smaller the better (i.e. target is min), by using Eqs (1)–(3) we normalize the 17 financial data for three categories, respectively. When the distinguishing coefficient ς and the adjustment coefficient η are set to 0.5, by Eqs (4)–(6), we can obtain three categories of the grey correlation matrix, as shown in Table 6.

We set the threshold value as 0.7 (Feng, Wang 2000; Wang 2008, 2009) to cluster financial indicators in three categories. The clustering results are shown in Table 7. Table 7 shows that profitability category is divided into two groups. The representative financial indicators we selected were P1 (ROA) and P4 (net profit margin after tax). The operating ability category is divided into four groups and selected representative financial indicators were O2 (accounts

Table 6. The grey correlation matrix on three categories

	Profitability					
	P1	P2	P3	P4	P5	
P1	1	0.7755	0.6388	0.6470	0.6518	
P2	0.7755	1	0.3770	0.3791	0.3803	
P3	0.6388	0.3770	1	0.9797	0.9679	
P4	0.6596	0.4037	0.9803	1	0.9863	
P5	0.6705	0.4181	0.9693	0.9865	1	
	Operating ability					
	O1	O2	O3	O4	O5	O6
O1	1	0.7446	0.6907	0.7492	0.6755	0.8189
O2	0.7383	1	0.8004	0.6832	0.8011	0.7918
O3	0.6693	0.7918	1	0.6795	0.8361	0.8245
O4	0.7313	0.6678	0.6795	1	0.5750	0.7058
O5	0.6544	0.7949	0.8377	0.5795	1	0.7858
O6	0.8092	0.7894	0.8294	0.7024	0.7909	1
	Solvency					
	S1	S2	S3	S4	S5	S6
S1	1	0.9687	0.7357	0.8130	0.7189	0.6263
S2	0.9696	1	0.7198	0.8255	0.7242	0.6234
S3	0.7153	0.6882	1	0.5550	0.8130	0.7794
S4	0.7892	0.7959	0.5315	1	0.5796	0.4815
S5	0.6829	0.6784	0.8048	0.5796	1	0.8482
S6	0.5585	0.5542	0.7696	0.4535	0.8482	1

receivable turnover), O3 (inventory turnover), O4 (average daily sales) and O6 (shareholder equity turnover). As for the solvency category, it is divided into three groups and selected representative financial indicators were S2 (quick ratio), S3 (debt ratio) and S5 (cash flow ratio). After the 9 representative financial indicators were selected, we then added the non-financial indicators of "total revenue" (TR) and "net sales" (NS), which have a total of 11 evaluation criteria to conduct a comprehensive performance evaluation and ranking for the 38 listed semiconductor companies in Taiwan.

Table 7. The classification of financial indicators and select the representative indicators

Category	Cluster	Financial indicators within the cluster	Representative indicators of each cluster
Profitability	C1	P1, P2	P1: ROA
	C2	P3, P4, P5	P4: Net profit margin after tax
Operating ability	C3	O2	O2: Accounts receivable turnover
	C4	O4	O4: Average daily sales
	C5	O6	O6: Shareholder equity turnover
	C6	O1, O3, O5	O3: Inventory turnover
Solvency	C7	S3	S3: Debt ratio
	C8	S1, S2	S2: Current ratio
	C9	S4, S5, S6	S5: Cash flow ratio

3.2.2. Calculation of the weights of the evaluation indicators with the entropy method

First, we normalize the 11 performance evaluation indicators using Eqs (1)–(3) to obtain the normalization matrix (Eq. (7)). Then, according to Eqs (7)–(10), we can obtain the entropy weights of the 11 performance evaluation indicators. Table 8 shows the results of the entropy weights for the efficient company and inefficient company groups, respectively. From the results in Table 8, we observe that the TR (total revenue) is the most important variable influencing a semiconductor company's performance, followed by NS (net sales).

Table 8. Results of the entropy weight for the 11 representative indicators

Group	P1	P4	O2	O3	O4	O6	S2	S3	S5	TR	NS
Efficient company	0.0888	0.0911	0.0886	0.0880	0.0863	0.0889	0.0885	0.0887	0.0889	0.1018	0.1005
Inefficient company	0.0895	0.0893	0.0900	0.0913	0.0895	0.0902	0.0907	0.0895	0.0896	0.0959	0.0945

3.2.3. The results of performance evaluation with the VIKOR-IGE model

In order to evaluate the performance and rank the 38 listed semiconductor companies (F1 to F38), this study proposes using a VIKOR-IGE model to evaluate the operating performance of the efficient and inefficient company groups, respectively. According to Section 2.4, we can construct the VIKOR-IGE model by using the following steps:

Step 1: According to the results of the globalized IGRA in Section 3.2.1, we select 9 representative financial indicators. From the results of the DEA-IG model in Section 3.1.3, we select two representative output variables. Therefore, this study uses 11 indicators to establish a performance evaluation model of the 38 semiconductor companies.

Step 2: Determine the ideal and negative ideal solution for efficient and inefficient companies, respectively.

Efficient companies group:

	P1	P4	O2	O3	O4	O6	S2	S3	S5	TR	NS
$f_i^* =$	{24.76,	293.54,	15.73,	20.95,	133.74,	2.77,	389.4,	62.56,	186.28,	406963311,	419537911}
$f_i^- =$	{–7.29,	–22.99,	3.73,	2.73,	17.42,	0.78,	35.4,	17.16,	–65.2,	4189005,	3100141}

Inefficient companies group:

$f_i^* =$	{14.16,	37.53,	11.61,	49.28,	122.03,	2.98,	797.98,	75.24,	183.97,	120430736	188742797}
$f_i^- =$	{–10.54,	–37.5,	3.08,	0,	0,	0.21,	27.92,	4.4,	–72.67,	226794	277339}

Step 3: Use Eqs (8)–(10) to calculate the entropy weight of 11 indicators. The results are shown in Table 8.

Step 4: Compute the values of S_j, R_j and Q_j (Q_j is measured with $v = 0.5$) for each company, by using Eqs (14)–(19). The results are shown in Table 9.

Step 5: According to Table 9, we separate and rank the efficient and inefficient companies, sorting by the values of S_j, R_j and Q_j. From the acceptable advantage, we can calculate the threshold values (Eq. (20)) as 0.1 and 0.0385 for the efficient and inefficient companies, respectively. The values of *S*, *R* and *Q* for the efficient and inefficient companies calculated by VIKOR-IGE model are shown in Table 9. When ranking by the VIKOR method in accordance with the *Q* values, the lower the value the better the performance of the company.

To rank the 38 semiconductor companies using the VIKOR-IGE model, we had to examine the *S*, *R* and *Q* values of each company, to see whether conditions 1 and 2 (Section 2.4) are satisfied. According to the results (Table 9) for the efficient companies in Taiwan for 2010, company F6 had the lowest value of *Q*, followed by company F16. However, company F6 did not have an acceptable advantage. This is because $Q^{[F16]} - Q^{[F6]} = 0.0775 < 0.1$. On the other hand, we observed that company F6 was acceptably stable in the decision-making process. Therefore, we proposed F6 and F16 as a set of compromise solutions. By comparing the *S*, *R* and *Q* values of each company, we can obtain the sorting result of the efficient companies, and cluster them into seven groups. The ranking is:

$$F6 \approx F16 \succ F10 \approx F36 \succ F2 \approx F8 \approx F14 \approx F22 \approx F33 \approx F38 \succ F29,$$

where: $A \succ B$ indicates that *A* is preferred to *B*; $A \approx B$ indicates that *A* and *B* are a set of compromise solutions. In addition, the inefficient companies can be clustered into 10 groups. The ranking is:

$$F26 \succ F27 \succ F23 \succ F25 \approx F31 \succ F15 \approx F18 \approx F19 \approx F21 \succ F4 \approx F7 \approx F12 \approx F28 \approx$$
$$F37 \succ F11 \approx F24 \succ F1 \approx F3 \approx F9 \approx F13 \approx F20 \succ F5 \approx F17 \approx F32 \succ F34 \succ F35.$$

Table 9. The values of S, R and Q for efficient and inefficient companies groups

Efficiency company group				Inefficiency company group			
Company	S_j	R_j	Q_j	Company	S_j	R_j	Q_j
F2	0.7337	0.0973	0.7929	F1	0.6592	0.0947	0.8187
F6	0.4796	0.0850	0.0383	F3	0.6851	0.0932	0.8146
F8	0.7024	0.1011	0.8594	F4	0.6527	0.0898	0.6867
F10	0.6947	0.0937	0.6282	F5	0.6751	0.0949	0.8451
F14	0.6569	0.1018	0.8105	F7	0.5919	0.0929	0.6807
F16	0.4547	0.0889	0.1158	F9	0.6565	0.0940	0.7959
F22	0.7804	0.0958	0.8200	F11	0.6379	0.0927	0.7391
F29	0.7232	0.1013	0.8959	F12	0.5571	0.0940	0.6604
F33	0.6589	0.1009	0.7862	F13	0.6769	0.0937	0.8175
F36	0.6451	0.0935	0.5466	F15	0.4982	0.0782	0.6305
F38	0.7115	0.1005	0.8534	F17	0.5529	0.0842	0.8550
				F18	0.7480	0.0936	0.6091
				F19	0.5731	0.0853	0.6282
				F20	0.6881	0.0902	0.7853
				F21	0.6479	0.0948	0.6217
				F23	0.6548	0.0908	0.4582
				F24	0.6161	0.0934	0.7258
				F25	0.5966	0.0879	0.5627
				F26	0.4028	0.0822	0.1559
				F27	0.5855	0.0760	0.2486
				F28	0.6214	0.0907	0.6651
				F30	0.5995	0.0926	0.6831
				F31	0.6104	0.0871	0.5607
				F32	0.6759	0.0947	0.8411
				F34	0.7117	0.0958	0.9164
				F35	0.7702	0.0959	1.0000
				F37	0.5703	0.0936	0.6695

According to the results of compromise solutions, the rankings of efficient and inefficient companies are shown in Table 10, respectively.

According to the ranking results in Table 10, the 11 efficient companies are divided into 1–4 grades, in which company F6 and F16 had the best operating performance among the 11 efficient companies, followed by company F10, F36 and finally, company F29. As for the 27 inefficient companies that can be divided into 1–11 grades, company F26 had the best operating performance among 27 listed inefficient companies, followed by company F35. Company F3 had the worst operating performance.

From an investor's perspective, efficient companies should be the first choice when making an investment decision. In view of this, companies F6 and F16 are the best choice in this group. If investors want to choose one of the inefficient companies to invest in, it is

Table 10. The ranking results of efficiency and inefficiency company groups

Efficiency company group		Inefficiency company group	
Rank	Company	Rank	Company
1	F6, F16	1	F26
2	F10, F36	2	F27
3	F2, F8, F14, F22, F33, F38	3	F23
4	F29	4	F25, F31
		5	F15, F18, F19, F21
		6	F4, F7, F12, F28, F37, F30
		7	F11, F24
		8	F1, F3, F9, F13, F20
		9	F5, F17, F32
		10	F34
		11	F35

recommended that they select the more highly ranked, such as companies F23, F25, F26, F27 and F31. Investors should avoid investing companies with inefficient and poor operating performance, such as companies F34 and F35. In particular, company F35 ranked last among the 27 inefficient companies in operating performance, showing that due to the company's production inefficiency, inefficient allocation of resources and poor operating performance, a management crisis will most likely occur. Therefore, investors should avoid investing in this company. Company F35's managers should understand their position in Taiwan's semiconductor industry, increase its resource allocation efficiency and improve operating performance, to achieve the goal of sustainable management.

Conclusions

In order to enable a company to achieve sustainable management, apart from making the most efficient use of resources, it is more important to ensure that the company can move toward better business performance. Evaluation of operating efficiency and business performance is not only an important issue for business managers, but also an important reference for investors who are determining their investment strategy. Therefore, this study uses IGRA, the entropy weight method, the DEA and VIKOR methods, and the proposed DEA-IG model and VIKOR-IGE model to conduct efficiency analysis and performance evaluation of Taiwan's 38 listed semiconductor companies in 2010, respectively. The results can serve as reference for management to set strategic and operational goals for companies, and performance evaluation results can provide investors with a reference for investment decision-making.

The results of the DEA-IG model show that two representative output variables (total revenue and net sales) and four representatives input variables (total assets, operating expenses, administrative expenses and inventory) were selected by using globalized IGRA, as the input and output indicators in the DEA model. Based on the results, Taiwan's 38 listed semiconductor companies are divided into two groups of 11 efficient companies and 27 inefficient companies.

We selected 9 representative financial indicators by using globalized IGRA, with two output indicators as performance evaluation indicators. Then we applied the entropy method to calculate the object weight of each indicator. The results showed that the "total revenue" is the most important indicator influencing a semiconductor company's performance. Finally, according to the above two groups, this study proposed a VIKOR-IGE model for evaluating and ranking each of the two groups. The final ranking results show that companies F6 and F16 are the best choices among the efficient company group, followed by company F10 and F36. And company F35 had the poorest operating performance and was ranked last in the inefficient companies group, suggesting that this company has the highest probability of failure in Taiwan's semiconductor industry.

Investors often choose investment targets based on past performance rankings to select a company, and do not consider the company's operating efficiency. However, the operational efficiency and business performance of a company are inexorably linked. Therefore, when the investors make investment decisions, we recommend that they choose companies with higher efficiency and operating performance as investment targets.

Acknowledgements

The authors would like to thank the National Science Council of the Republic of China, Taiwan for financially supporting this research under Contract No. NSC 101-2410-H-275-002.

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