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Sustainability Assessment of Taiwan's Semiconductor Industry: A New Hybrid Model Using Combined Analytic Hierarchy Process and Two-Stage Additive Network Data Envelopment Analysis

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Abstract: Sustainable development has become the biggest concern of the semiconductor industry, which plays a vital role not only in technology breakthroughs, but also by serving as an enabler for sustainability. This study combines Analytic Hierarchy Process (AHP) and additive network Data Envelopment Analysis (DEA) to measure the sustainable performance which are derived from business growth stage and energy utilization stage through the parametric linear program. Meanwhile, this method makes up the disadvantage of the weighting technique used additive decomposition approach to the two-stage network and avoids biasing toward the second stage. The findings demonstrate that Taiwan's semiconductor manufacturing sector has exhibited a steady increase in its overall trend of sustainability performance. According to the stage-level performance results, the performance of business growth is better than energy utilization. However, the changing trend of overall sustainability performance is through a steady increase from environmental efficiency and not from economic efficiency.

Keywords: sustainability assessment; Data Envelopment Analysis (DEA); semiconductor industry

1. Introduction

With the dynamic evolution of the information and communications technology (ICT) industry, in which products such as computers, and integrated circuits (ICs) are playing a more vital role. With the increasing popularity of new electronic products related to mobile devices and artificial intelligence our safe and living environments have a high relevance with the quality and reliability of these products. Semiconductors appear to be the soul of electronic products, and the semiconductor industry produces a range of microelectronic components, so-called "chips," that are seen as many of the key components for economic development. According to WSTS (World Semiconductor Trade Statistics), worldwide semiconductor revenue in the second quarter of 2018 reached US$117.9 billion for year-to-year growth of 20.5%. The Taiwan Semiconductor Industry Association (TSIA) survey showed that Taiwan's ICs revenue in 2018 is expected to reach US$85.8 billion (5.9% growth from 2017). Hatami-Marbini and Kangi [1] indicated that the environmental and social externalities associated with semiconductor manufacturing are likely to increase due to the usage of semiconductors devices becomes more prevailing across different varieties of industries.

To the semiconductor industry, sustainable development is a critical concern. Due to the hundreds of high-purity organic and inorganic waste disposal produced in manufacturing semiconductors have to be treated environmentally [2]. Semiconductor industries play an important role not only in unceasingly technology breakthroughs, but also by serving as an enabler for sustainability. The challenges from industry competition [3,4], political and economic volatilities [5], and the operational impact of climate change [6] cannot be avoided. To implement sustainability practices, Taiwan should reconsider how to reduce energy consumption while maintaining economic growth. This paper is concerned with measuring efficiencies during the sustainable operations of the semiconductor industry.

Given the prevalence of the sustainability issue in the semiconductor industry, prior research has focused on the dimension of sustainable capacity of technical learning [7], green supply chain [6], capacity planning [8], and waste management [2]. The difficulty in attaining such a sustainable society is that prior literatures do not have a methodology to accurately assess economic development and pollution reduction in a unified manner, because recent growth has been usually associated with various types of pollutions [9]. Proponents of environmental protection worry about pollution, while opponents argue that controlling the pollution can reduce the pace of economic growth [10] by limiting the operations of manufacturing industries. This issue can be addressed by the Data Envelopment Analysis (DEA) technique, because DEA applies to problems with multiple inputs and multiple outputs [11], while also considering undesirable outputs. Thus, it can evaluate the sustainability performance more precisely [12,13].

In order to assess sustainable development, previous studies have developed the variations of DEA [12–14]. As stated above, the application of DEA provides a tool for the comprehensive assessment of the environmental impacts and operational performances of multiple DMUs (Decision Making Units). Wu et al. [15] examined environmental efficiency of a two-stage DEA system with undesired outputs. The two-stage system consists of two parts: a production subsystem and a pollution treatment subsystem. Hatami–Marbini et al. [16] developed a flexible cross-efficiency evaluation methodology based on DEA for identifying supplier performance.

Motivated by those findings, this study presents a sustainability measurement framework in Taiwan's semiconductor industry through the additive efficiency decomposition approach for measuring the efficiency of networks. The aim of this study lies not only in the generalization of the DEA filed, but also in utilizing it from the Taiwan semiconductor industry. Our application differs from prior DEA studies on the semiconductor sector in three essential ways as noted below.

Firstly, with the deeper development of economic globalization, the sustainability practice has become an inevitable trend. Semiconductor industries play an important role by serving as an enabler for sustainability in Taiwan. However, few studies to date have conducted a sustainability assessment in the context of Taiwan's semiconductor industry. Therefore, our paper looks to fill this gap in the literature. Through our modeling framework, these individual-level efficiency scores provide insight into how the impacts which are derived from business growth or energy utilization are generated in the semiconductor industry.

Secondly, this study proposes a new hybrid model to make up for some shortcomings in weight through the additive efficiency decomposition approach [17]. The paper provides a comprehensive view of the relationship between overall efficiency and stage efficiencies under varying weights. This extension is essential in the DEA field. It is important to note here that in contrast to existing DEA literature, we solve the non-linear DEA model directly, without resorting to reducing it to a variant of classical linear DEA model.

Thirdly, MCDM (Multiple Criteria Decision Making) methods are used in this study for finding the "appropriate" pair of weights. This study uses the Analytic Hierarchy Process (AHP) method to identify the "optimal" weights in the model. In other words, AHP is used to examine the importance of the two-stage performance whereby the overall efficiency is defined as a weighted average of stage efficiencies and the weights are used to reflect the relative importance of individual stages. We update the model and expand the application to the semiconductor industry by integrating the economic and ecological aspects of this study.

The remainder of this paper is organized as follows. Section 2 provides a review of the DEA literature on sustainability and two-stage DEA models. Section 3 introduces the methodology of the new hybrid model using combined AHP and two-stage additive network DEA. Section 4 analyzes the sustainability assessment of the semiconductor industry in Taiwan. Finally, Section 5 presents the conclusion.

2. Assessment of Sustainability

Enhancing competitiveness and sustainability has been pursued by many if not all semiconductor manufacturers [18]. Hung, He and Lu [4] evaluated the operating performances through dynamic DEA. Hatami–Marbini et al. [19] proposed a four-step bounded fuzzy DEA model as an efficiency tool to measure relative efficiencies. Hsu [3] integrated DEA and improved grey relational analysis (IGRA) to measure the efficiency. Wang and Ho [20] combined the forecasting model of Grey theory and DEA to help the semiconductor industry to select strategy alliance partners. Tsai, Wu, Chen, Chen, and Ye [5] adopted traditional DEA models to explore benchmark corporations. Li et al. [21] generalized a three-stage DEA model to evaluate the efficiency of innovation.

Because environmental protection and sustainable development are both important topics to discuss, the semiconductor industry has increasing concerns about the sustainability of the environment [2]. Furthermore, due to rapid economic development, the increasingly severe effects of environmental pollution have attracted widespread attention all over the world [22]. The semiconductor industry assimilates green management into its business and implements continuous improvement projects in the areas of climate change, energy management, water management, waste management, and air pollution control. The goal is to facilitate coexistence and mutual prosperity between semiconductor industry businesses and the environment [23].

There are various approaches across the literature regarding the assessment of sustainability [1,9]. Hatami-Marbini and Kangi [1] presented a case study from the semiconductor industry to demonstrate the applicability of the proposed model and the efficacy of the procedures and algorithms [1]. Sueyoshi and Yuan [9] set up a new use of a DEA intermediate approach to evaluate the sustainability of Asia nations.

Production (with pollutant byproducts called undesirable outputs) and pollution treated as a two-stage system have aroused increasing attention in the sustainability management field. Undesirable factors have been taken into account in measuring the efficiency of suppliers [24], eco-efficiency [25,26], and resource and environmental efficiency [15,27]. The literature has also presented DEA efficiency evaluation by considering undesirable factors, and undesirable factors can be regarded as inputs or undesired outputs in the DEA models [13,22,28]. Scholars have developed different techniques to deal with undesirable outputs in DEA [29]. Undesirable outputs are inevitably produced along with desirable outputs [22].

Inefficient economic activities may result in excessive use of resources and high levels of pollution emissions due to production processes rely on resource inputs [30]. Furthermore, environmental efficiency cannot be separated from economic efficiency. Thus, the indicators in this context are necessary for policymaking [31]. While the previous studies have focused on development of environmental measures [27,32], this study propose a method that incorporates the financial and ecological aspects of sustainability. Figure 1 depicts the empirical framework of assessing process sustainability in this study. For our study of semiconductor firms' sustainability performance in Taiwan, we divide the network process into two sub-processes: the business growth process and the energy utilization process. The former one focuses on applying inputs to produce desirable outputs and undesirable outputs, while the following one focuses on the disposal of pollution and waste that are produced in the former.

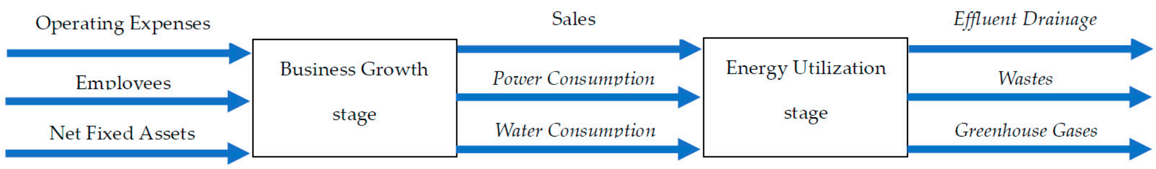

Figure 1. Empirical framework of assessing process sustainability. Note: italics are used for the undesirable items.

3. Research Design

3.1. Framework of the Performance Evaluation of the Semiconductor Industry

Sustainable development and sustainability evaluation have been of great interest to both academia and practitioners in the past decades [33]. It is clear that large-scale production leads to high levels of environmental pollution. Accordingly, the decision maker looks at the weight of sub-processes differently in the presence of sustainability expectations. MCDM methods can support decision-makers in this process [34,35], and used for finding the "appropriate" pair of weights. In other words, we look to identify the "optimal" weights for the two-stage performance. The analysis of complex decisions involves the evaluation of activities using multiple criteria to determine the best alternative action. AHP is the popular method in decision making, which only needs the decision makers to compare each pair of objects and provide their preference values. Since it was first introduced by Saaty [36], AHP has been applied in many fields [35,37–39]. He and Zhang [38] proposed a model integrated factor analysis (FA), DEA, with AHP for supplier selection. Kim, Jeon, Cho and Kim [39] used the AHP to analyze the relative importance and performance of individual environmental management tasks in the hospital. The relevant criteria and their relative importance are elicited from the decision makers via pairwise comparisons of the AHP technique. The standard processes of the AHP are also utilized here, such as inconsistency checking and resolution [40].

Based on the literature reviews [12,13,22], two-stage DEA is the most often used tool in sustainability assessment. Even though this method is useful for efficiency measurement, it suffers from many drawbacks. One major drawback of DEA is that it does not account for the weight of sub-processes in deriving efficiency scores. To account for this limitation, we employ the AHP procedure to identify the optimal weights for the two-stage performance. We consider a two-stage additive network DEA model to assess the performance of the semiconductor industry and propose an efficient algorithm to solve it. Similar to Guo, Abbasi Shureshjani, Foroughi and Zhu [17], we assume that the overall efficiency of a two-stage network is a product of the efficiencies of two individual partners. Unlike Guo, Abbasi Shureshjani, Foroughi and Zhu [17], this study expends the application of a two-stage model with multiple objectives where the goal of the decision maker is to maximize the product of the efficiencies of the individual stages.

3.2. Data Collection and Descriptive Statistics

Data on 15 companies in the semiconductor industry for the period 2014–2017 were obtained from their CSR (Corporate Social Responsibility) reports published in the Market Observation System (MOPS) of Taiwan Stock Exchange (TSE). CSR reports follow widely-adopted global guidelines set by the Global Reporting Initiative for the transparent disclosure of corporate values and performances. The period examined corresponds to sustainable development issues that are of most concern in the semiconductor industry, whereby the CSR report is voluntary information disclosure. Disclosing environmental information can assist people understand the impact of a company's product on the environment and further help supervise corporate social responsibility. The CSR report, which including continuous improvement projects in the areas of climate change, energy management, water management, waste management, and air pollution control, is a bellwether response to the United Nations SDGs (Sustainable Development Goals) in the economic, environmental, and social dimensions, which support global sustainability through concrete action. Data reflecting financial performances of 15 companies are obtained from the Taiwan Economic Journal database.

This study follows previous works [12–15,25,27,41–43] and assume that the first stage of the business growth process uses labour, operating expenses, and net fixed assets to produce sales, power consumption, and water consumption that serve as intermediate outputs. Labour is measured as the number of full-time employees. Operating expenses are measured as the expenditure that a business incurs as a result of performing its normal business operations. Net fixed assets are the residual difference between assets and liabilities. Power consumption and water consumption serve as undesirable outputs to the first stage of production. Power consumption is measured as the amount of electric power mainly used in manufacturing by process equipment and facility systems. This output (sales, power and water consumption) from the first stage determines business growth outcomes from the operating facility using the input financial and labour resources in the first stage. The second stage of energy utilization focuses on reducing the pollution of the environment and the management of natural resources. The second stage of the energy utilization process covers sales, power consumption, and water consumption produced from the first stage to produce a set of effluent drainage, wastes, and greenhouse gases as undesirable by-products from such production [44]. Table 1 provides descriptive statistics on the inputs and outputs.

Table 1. Descriptive statistics of input, intermediate, and output variables.

	Mean	Standard Deviation	Minimum	Maximum
Inputs				
Operating Expenses (million NT$)	13,336	24,063	323	109,267
Employees (person)	13,235	21,537	267	87,366
Net Fixed Assets (billion NT$)	96	232	0.447	1062
Intermediates				
Sales (million NT$)	104,413	218,447	5368	977,447
Power Consumption (TW·h, terawatt hour)	998	2185	5	10,829
Water Consumption (ton)	5,485,035	9,714,591	27,769	45,200,000
Outputs				
Effluent Drainage (ton)	3,719,390	6,092,671	27,524	29,400,000
Wastes (ton)	29,755	70,346	47	361,969
Greenhouse Gases (ton)	644,460	1,232,272	2700	5,700,000

3.3. Two-Stage Additive Network DEA Model

Economic activities use material resources, labor, and capital to produce desirable goods and services, but simultaneously trigger additional effects on the natural environment and inevitably result in the generation of pollution, such as greenhouse gases and wastewater [32,45]. Economic efficiency reflects the ability of a production unit to obtain maximal output from a given set of inputs and the production technology [15,37]. However, it does not imply resource and environmental efficiencies [15,31,46].

The solutions of the environmental efficiency measures are complicated [27,41,42], especially for the cooperative ecological efficiency measure, because they represent non-linear programming problems [12,31]. The rational methods to address undesirable elements have been introduced into these environmental efficiency measures [13,22,28], and more reasonable and straightforward ecological efficiency measures have been investigated [47].

Previous studies note that two-stage DEA models are more efficient than single-stage ones since their discriminatory power is higher [26,48,49]. The traditional DEA model neglects the connectivity of internal economic activities and cannot express the management messages of those activities. The internal economic activities are considered to be a "Black Box". This study adopts the network DEA performance evaluation model [50,51] to evaluate operational management performance and changes in the performance efficiency of sustainable operations of the selected semiconductor companies in the following network activities. Efficiency can be measured more appropriately by using the two-stage additive network DEA approach [17]. When considering the difference between input slack and output slack, this study uses "input-oriented efficiency" to evaluate the performance of the semiconductor industry (as DMUs).

This study first considers the process that deals with $DMU_j(j = 1, \cdots, n)$. We denote the multipliers for the above factors as: V_q is the weight for the input component m_q entering the process at the beginning of stage 1; and u_h is the weight for the output component r_h flowing from stage 1 and is also the multiplier for that same component as it becomes an input to stage 2. At each term, x_k is the weight for the input component o_k^2 entering the process at the beginning of stage 2, and z_s is the weight for the output component n_s at stage 2. Therefore, this study defines the input-oriented efficiency of stages 1 and 2 by solving the program as follows:

$$\begin{array}{l} \rho_1 = \sum_{h=1}^{H} u_h r_{ho} / \sum_{q=1}^{Q} v_q m_{qo}, \\ \rho_2 = \sum_{s=1}^{S} z_s n_{so} / \left(\sum_{h=1}^{H} u_h r_{ho} + \sum_{k=1}^{K} x_k o_{ko}^2 \right) \end{array} . \tag{1}$$

This study adopts the network DEA performance evaluation model [17]. Under the additive efficiency decomposition approach, the overall efficiency score can be defined as a weighted average of the two-stage efficiencies as follows:

$$\rho_o^* = w\rho_1 + (1 - w)\rho_2. \tag{2}$$

Thus, we can write the overall efficiency ρ_o^* in the form:

$$\rho_o^* = max\left[w \sum_{h=1}^{H} u_h r_{ho} / \sum_{q=1}^{Q} v_q m_{qo} + (1 - w) \sum_{s=1}^{S} z_s n_{so} / \left(\sum_{h=1}^{H} u_h r_{ho} + \sum_{k=1}^{K} x_k o_{ko}^2 \right) \right]. \tag{3}$$

We adopt the network DEA performance evaluation model [52] and then set out to optimize the overall efficiency ρ_o^* of the multistage process, subject to the restrictions that the individual measures ρ_q must not exceed unity, or under the linear programming format after making the usual Charnes and Cooper transformation. This study defines the input-oriented overall efficiency as a ratio ranging between 0 and 1, which attains a value of 1 when all slacks are zero [53]. This objective function value is also unit-invariant. Following [17], we let $d = 1/\sum_{q=1}^{Q} v_q m_{qo}$ and set $\widetilde{u_h} = du_h, \widetilde{v_q} = dv_q, \widetilde{z_s} = dz_s, \widetilde{x_k} = dx_k$. The following input-oriented VRS-based network DEA model for estimating the input ρ_o^* of a firm in envelopment is in converted form as:

$$\begin{array}{l} \rho_o^* = max\left[w \sum_{h=1}^{H} \widetilde{u_h} r_{ho} + (1 - w) \sum_{s=1}^{S} \widetilde{z_s} n_{so} / \left(\sum_{h=1}^{H} \widetilde{u_h} r_{ho} + \sum_{k=1}^{K} \widetilde{x_k} o_{ko}^2 \right) \right], \\ s.t. \\ \left(\sum_{h=1}^{H} \widetilde{u_h} r_h^j \right) \leq \sum_{q=1}^{Q} \widetilde{v_q} m_q^j, \\ \left(\sum_{s=1}^{S} \widetilde{z_s} n_s^j \right) \leq \left(\sum_{h=1}^{H} \widetilde{u_h} r_h^j + \sum_{k=1}^{K} \widetilde{x_k} o_k^{2j} \right) \forall j, \\ \sum_{q=1}^{Q} \widetilde{v_q} m_{qo} = 1 \\ \widetilde{u_h}, \widetilde{v_q}, \widetilde{z_s}, \widetilde{x_k} \geq 0; 0 \leq w \leq 1, \forall h, q, s, k \end{array} . \tag{4}$$

If the optimal solution for (4) satisfies $\rho_o^* = 1$, then DMU_o is called overall input-oriented efficient or briefly overall efficient. We let $f = 1/\sum_{h=1}^{H} \widetilde{u_h} r_h^j + \sum_{k=1}^{K} \widetilde{x}_k o_k^{2j}$ and set $z'_s = f\widetilde{z}_s, x'_k = f\widetilde{x}_k$ Model (4) is then converted to:

$$\begin{array}{l} \rho_o^* = max\left[w\sum_{h=1}^{H} \widetilde{u_h} r_{ho} + (1-w)\sum_{s=1}^{S} z'_s n_{so}\right], \\ s.t. \\ \left(\sum_{h=1}^{H} \widetilde{u_h} r_h^j\right) \leq \sum_{q=1}^{Q} \widetilde{v}_q m_q^j, \\ \left(\sum_{s=1}^{S} z'_s n_s^j\right) \leq \left(\sum_{h=1}^{H} \widetilde{u_h} r_h^j + \sum_{k=1}^{K} x'_k o_k^{2j}\right) \forall j, \\ \sum_{q=1}^{Q} \widetilde{v}_q m_{qo} = 1 \\ f\sum_{h=1}^{H} \widetilde{u_h} r_h^j + \sum_{k=1}^{K} x'_k o_k^{2j} = 1 \\ \widetilde{u_h}, \widetilde{v}_q, \widetilde{z}_s, \widetilde{x}_k \geq 0; 0 \leq w \leq 1, f > 0, \forall h, q, s, k \end{array} . \tag{5}$$

For each fixed w, the above model can be solved by a sequence of linear programs by varying f and searching for the best (global) solution. We present the bounds of stage efficiency scores for all weights of the maximal efficiency scores for the first stage and the second stage as:

$$\begin{array}{l} \bar{\rho}_1 = max\sum_{h=1}^{H} u_h r_{ho} / \sum_{q=1}^{Q} v_q m_{qo}, \\ \bar{\rho}_1 = max\sum_{h=1}^{S} Z_s n_{so} / \left(\sum_{h=1}^{H} u_h r_{ho} + \sum_{k=1}^{K} x_k o_{ko}^2\right), \ subject\ to\ the\ constraints\ of\ (5) \end{array} . \tag{6}$$

Next, the minimum efficiency scores for the first stage and the second stage are:

$$\begin{array}{l} \underset{-1}{\rho} = max\sum_{h=1}^{H} u_h r_{ho} / \sum_{q=1}^{Q} v_q m_{qo} \\ s.t.\sum_{s=1}^{S} z_s n_{so} / \left(\sum_{h=1}^{H} u_h r_{ho} + \sum_{k=1}^{K} x_k o_{ko}^2\right) = \bar{\rho}_2, \ subject\ to\ the\ constraints\ of\ (5) \\ \underset{-2}{\rho} = max\sum_{s=1}^{S} z_s n_{so} / \left(\sum_{h=1}^{H} u_h r_{ho} + \sum_{k=1}^{K} x_k o_{ko}^2\right) \\ s.t.\sum_{h=1}^{H} u_h r_{ho} / \sum_{q=1}^{Q} v_q m_{qo} = \bar{\rho}_1, \ subject\ to\ the\ constraints\ of\ (5) \end{array} . \tag{7}$$

Note that the optimal multipliers obtained from (5) may not be unique [17], implying that ρ_1 and ρ_2 are not unique. Therefore, in the spirit of [17], the overall efficiency score for DMU_j can be calculated by model (3), and the maximum achievable values of ρ_1 and ρ_2 can be determined via model (8), respectively.

$$\begin{array}{l} \rho_1^+ = max\sum_{h=1}^{H} u_h r_{ho} / \sum_{q=1}^{Q} v_q m_{qo} \\ s.t.w\sum_{s=1}^{S} z_s n_{so} / \sum_{h=1}^{H} u_h r_{ho} + (1-w)\sum_{k=1}^{K} x_k o_{ko}^2 = \rho_0^*, \ and\ the\ constraints\ of\ (5) \\ \rho_2^+ = max\sum_{s=1}^{S} z_s n_{so} / \left(\sum_{h=1}^{H} u_h r_{ho} + \sum_{k=1}^{K} x_k o_{ko}^2\right) \\ s.t.w\sum_{s=1}^{S} z_s n_{so} / \sum_{h=1}^{H} u_h r_{ho} + (1-w)\sum_{k=1}^{K} x_k o_{ko}^2 = \rho_0^*, \ and\ the\ constraints\ of\ (5) \end{array} \tag{8}$$

On the other hand, the minimum of ρ_1 and ρ_2 can be determined via model (9), respectively.

$$\begin{array}{l} \rho_1^- = \frac{\rho_0^* - (1-w)\rho_2^+}{w}, \\ \rho_2^- = \frac{\rho_0^* - (1-w)\rho_1^+}{w}, \end{array} . \tag{9}$$

Note that $\rho_1^- = \rho_1^+$ if and only if $\rho_2^- = \rho_2^+$. If $\rho_1^- = \rho_1^+$ and $\rho_2^- = \rho_2^+$, then stage efficiencies ρ_1 and ρ_2 are uniquely determined via model (5). Furthermore, the upper and lower values of the new overall efficiencies are equal when $\rho_1^- = \rho_1^+$ or $\rho_2^- = \rho_2^+$. This indicates unique stage efficiency, and the new overall efficiency is thus uniquely determined.

4. Empirical Results

4.1. Overview of the Semiconductor Industry's Overall and Stage-Level Performances

This section describes the evaluation of the efficiencies of 15 companies in Taiwan's semiconductor manufacturing sector. The overall efficiency of the model is the proposed sustainability efficiency, and it remains unchanged, indicating that the variation in the original overall efficiency is a result of changing alpha only when stage efficiencies are unchanged [17]. As it stands, the model is able to identify the best performers and provide realistic and applicable target objectives and peer groups. Table 2 presents the results of the AHP method to identify the "optimal" weights by ten experts in the semiconductor manufacturing field for the two-stage performance, and this method is able to resolve the problem under which the two management processes may influence overall performance. The weight via the AHP method gives a reasonable evaluation of the DMUs' overall efficiencies, and it also provides more information to facilitate improvement. Thus, the weights via MCDM method seem to be a more scientific process for environmental assessments. The measurements considering the intensity of importance between the two stages are made based on the standard AHP scale from 1 to 9. The relative importance weights from a set of criteria via pairwise comparisons are 0.575 in the business growth stage and 0.425 in the energy utilization stage, as shown in Table 2. This suggests an unequal division of weights among these two stages of assumptions, especially when individual effects are assessed.

Table 2. Weight scores of the two stages.

AHP	Weight	Expert No.									
		1	2	3	4	5	6	7	8	9	10
F	0.575	0.500	0.500	0.750	0.750	0.333	0.333	0.667	0.667	0.750	0.500
S	0.425	0.500	0.500	0.250	0.250	0.667	0.667	0.333	0.333	0.250	0.500

Following [17], we apply the new overall efficiency index to address some pitfalls in the weighted additive efficiency decomposition. Table 3 lists the 15 performers in overall management estimated by applying a non-parametric DEA approach by [17]. These results, which use the "optimal" weights in Table 3, indicate that the overall performance efficiency scores are 0.638, 0.630, 0.643, and 0.666 in the period 2014–2017. The changing trend of the overall sustainability performance of Taiwan's semiconductor manufacturing sector shows a steady increase.

As the existing literature explains, the two-stage model distinguishes the information from each stage that cannot be recognized in the overall efficiency [54]. Calculating the two component efficiencies as well as the overall efficiency can assist an organization in determining the sources of inefficiency [43]. First, the environmental efficiencies of the overall semiconductor industry are lower than economic efficiencies from 2014 to 2017. Apart from environmental efficiencies, we notice that half of the DMUs perform well in economic efficiency, with an average efficiency value above 0.9. Financial performance is mainly determined by revenue growth and consistent improvement in profitability, and financial performance is the key to corporate sustainability.

The efficiency scores in the first stage are 0.787, 0.766, 0.781, and 0.769 during year 2014 to 2017. The efficiency of the business growth stage has remained constant for the whole semiconductor industry. On the other hand, the environmental efficiency fluctuates throughout a steady increase. The efficiency scores in the second stage are 0.456, 0.465, 0.473, and 0.541, respectively. In other words, the overall sustainability efficiency of the semiconductor industry increases due to environmental efficiency and not from economic efficiency. As a matter of comparison, the environmental efficiency within this industry may be significantly rising, because of the increasingly strict environmental protection regulations and the significant increase in demand for raw materials and the expansion of advanced production processes in the domestic semiconductor industry.

We now decompose these two different efficiency scores concerning individual stage and time effects. This model allows us to quantify contributions of the two stages (both desirable and undesirable factors). Table 3 presents the results for the efficiency scores of the two stages. In the two-stage approach, a DMU is efficient if and only if it is both efficient in the business growth stage and energy utilization stage. Thus, no firm is efficient, and this information is of value, because it implies there is still much room for improvement in sustainability efficiency. According to the efficiency results of the individual stage-level process, thirteen of the fifteen companies exhibit better business growth and energy utilization from year 2014 to 2017.

This study evaluates environmental efficiency by incorporating environmental impacts as undesirable outputs generated by the production process. These results reveal that generally the environment pollution generated by Taiwan's semiconductor manufacturing sector is not well controlled. For the sustainability concepts that can reduce undesirable outputs from the given inputs and desirable outputs, it is imperative to act within the scope of current production technology [31]. As such, the air pollution brought about by the semiconductor manufacturing industry is composed mainly of volatile organic compounds as well as acidic and alkaline gases. Hence, the empirical evidence suggests that the inefficiency levels of undesirable output show that greenhouse gases significantly reduce environmental efficiency, meaning there is still huge space for improvement.

4.2. Individual-Level Performance in the Semiconductor Industry

In order to further illustrate individual-level performance, we apply a benchmarking method applied on the companies to find the best role-models so that others can learn from them with an aim at effectively improving their own operating performance, as well as to analyze the gap between them and the role-model firms with the added goal of strengthening competitive advantages and operating performance through continuous improvement [55]. GETI (0.957, 0.985, 0.923), FSTC (0.982, 0.992, 0.969), VTSC (0.923, 0.982, 0.850), and WWC (0.883, 0.853, 0.919) have high relative efficiency in "overall efficiency", "operational efficiency", and "environmental efficiency" and thus could be used as a reference by other companies.

Good overall performance may not represent good operational management process performance [49] or good environmental management performance. For example, the overall efficiencies of UMC and EM show an average of 0.558 and 0.554 during the period of this study. There seems to be no significant difference between the two companies. It is worth noting that EM (0.998) achieves the highest operational efficiency scores in the efficiencies of the individual stages, whereas UMC achieves the lowest score (0.281). Unless environmental measures are explicitly incorporated in an aggregate measure, economic performance measures will not accurately reflect their impact [14]. The hybrid approach using combined AHP and additive DEA is useful for evaluating the additive efficiency decomposition provided from the valuable information of the top management team (TMT). From this discussion, we can conclude that it is crucial to integrate company internal resource for achieving long-term operational target aimed at promoting sustainable development.

If an individual company succeeds at improving its recycling capabilities, then it will achieve high environmental efficiency scores. For a company to deliver high sustainability development, it should not just aim at improving recycling capabilities, but also look to enhance the synergies between economic growth and environmental protection. We may conclude that as the semiconductor industry continues to grow, its requirements for sustainable measures such as energy conservation, carbon reduction, water savings, and waste reduction will all continue to increase as well, and thus companies must devote more attention to the issue of environmental sustainability.

Table 3. Efficiency scores for the performance of the DMUs.

DMU	OERR				FERR				SERR				OERR	FERR	SERR
	2014	**2015**	**2016**	**2017**	**2014**	**2015**	**2016**	**2017**	**2014**	**2015**	**2016**	**2017**		**Mean**	
United Microelectronics Corp. (UMC)	0.549	0.546	0.532	0.604	0.290	0.290	0.261	0.281	0.866	0.860	0.863	1	0.558	0.281	0.897
Delta Electronics (DELTA)	0.605	0.552	0.561	0.547	0.993	0.906	0.922	0.895	0.131	0.120	0.119	0.122	0.566	0.929	0.123
Taiwan Semiconductor Manufacturing Corp. (TSMC)	0.486	0.502	0.520	0.578	0.697	0.715	0.742	0.233	0.228	0.242	0.248	1	0.522	0.597	0.430
Macronix International Corp. (MIC)	0.492	0.517	0.728	0.787	0.369	0.415	0.880	1	0.641	0.641	0.541	0.526	0.631	0.666	0.587
Winbond Electronics Corp. (WEC)	0.413	0.427	0.427	0.414	0.546	0.562	0.577	0.530	0.252	0.263	0.245	0.272	0.420	0.553	0.258
Tatung Corp. (TC)	0.306	0.281	0.260	0.239	0.535	0.491	0.452	0.414	0.025	0.023	0.026	0.025	0.271	0.473	0.025
Nanya Technology Corp. (NTC)	0.620	0.546	0.519	0.566	0.961	0.790	0.583	0.639	0.203	0.247	0.440	0.477	0.563	0.743	0.342
Elan Microelectronics (EM)	0.557	0.552	0.551	0.557	1	1	0.994	1	0.015	0.006	0.010	0.016	0.554	0.998	0.012
Green Energy Technology Inc. (GETI)	1	0.912	0.942	0.973	1	0.939	1	1	1	0.879	0.871	0.940	0.957	0.985	0.923
Formosa Sumco Technology Corp. (FSTC)	0.995	0.982	0.984	0.965	1	0.967	1	1	0.989	1	0.965	0.922	0.982	0.992	0.969
Nuvoton Technology Corp. (NTC)	0.685	0.684	0.673	0.662	0.964	0.997	1	1	0.345	0.303	0.274	0.248	0.676	0.990	0.292
Vanguard International Semiconductor Corp. (VTSC)	0.783	0.969	0.943	0.995	0.941	0.998	1	0.992	0.591	0.934	0.874	1	0.923	0.982	0.850
Sino-American Silicon Products Inc. (SASPI)	0.673	0.607	0.570	0.643	0.991	0.914	0.764	1	0.284	0.232	0.334	0.207	0.623	0.917	0.264
Chipbond Technology Corp. (CTC)	0.562	0.522	0.528	0.533	0.736	0.643	0.650	0.679	0.348	0.375	0.380	0.354	0.536	0.677	0.364
Wafer Works Corp. (WWC)	0.848	0.855	0.900	0.927	0.787	0.859	0.897	0.868	0.922	0.851	0.903	1	0.883	0.853	0.919
Mean	0.638	0.630	0.643	0.666	0.787	0.766	0.781	0.769	0.456	0.465	0.473	0.541	0.644	0.776	0.484

Note: "OERR", "FERR", and "SERR" denote overall efficiency score, first-stage efficiency score, and second-stage efficiency score, respectively.

4.3. Efficiency Analysis of the Comparison under the Traditional DEA Approach

As a matter of comparison, Table 4 presents the results of the traditional two-stage DEA approach, with the first-stage efficiency scores being 0.754, 0.761, 0.736, and 0.794 in the period 2014–2017. The efficiency of the business growth stage has remained constant. The second-stage efficiency scores are 0.552, 0.566, 0.557, and 0.576 in the same period, which are consistent with the empirical results of Section 4.1, showing that the performance of business growth is better than energy utilization.

According to the analysis given above, similar conclusions can be reached by comparing the distribution of the number of efficient DMUs in different years, indicating there is great potential for improvement in the production process comprising multiple stages. It is also worth noting that environmental efficiency scores in the traditional DEA approach tend to from a higher assessment, so that the semiconductor manufacturing sector may be overestimating its performance in the development of environmental protection. Although we find a similar result that the changing trend of overall sustainability performance still exhibits a steady increase, the problem of the decision over the weights remains unresolved. Table 4 shows the overall performance efficiency scores are changing according to varying weights (with alpha = 1 ... 9). These results suggest not only the impacts of variables that are selected by the model, but also the impacts of varying weights.

We now compare the decision of the weights in this study with previous studies. The efficiency was calculated, for example, as the arithmetic average of stage efficiency [56], or through a set weight of $\alpha = 0.5$ [57], common set of weights [26]. Prior literature demonstrated the differences between the product of stage efficiency scores and weights [58]. However, the overall efficiency scores are changing according to varying weights. The overall efficiency's variation should reflect changes in the stage efficiencies, and we recommend using the newly-defined overall efficiency after the calculations are performed. Decision makers can choose the stage efficiencies to maximize the new overall efficiency score [17]. From the previous analysis, one can gain insights concerning the overall score is a function of the score at each stage of production.

Under the weights of the AHP method, we examine whether any unique efficiency decomposition exists. We assume the overall efficiency of a two-stage network is the product of the efficiencies of two individual parts. In other words, our approach provides a comprehensive view of the relationship between the overall efficiency and the stage efficiencies under the varying weights.

For illustration purposes, we set $w = \frac{j}{10}$, $j = 1 \ldots 9$, and when the parameter $f_t = 1/\rho_1 - 0.01 * t$. approaches the lower bound of 0, the algorithm ends. We treat the maximal value from the t calculations as the global optimal solution. The upper and lower values of the new overall efficiency are equal when $\rho_1^- = \rho_1^+$ or $\rho_2^- = \rho_2^+$. This indicates unique stage efficiency, and the new overall efficiency is uniquely determined. Guo, Abbasi Shureshjani, Foroughi and Zhu [17] noted that the information on the overall and stage efficiencies under various weights could be useful in empirical applications. That is the exciting aspect of the differentiation between previous analyses that incorporate the specific weight into the additive DEA model and attempt to decompose these two different efficiency scores concerning individual and time effects.

Table 4. Efficiency scores by the traditional network Data Envelopment Analysis (DEA) approach.

DMU	FERR					SERR					OERR															
											alpha = 1				alpha = 2				alpha = 3				alpha = 4			
	2014	2015	2016	2017	Mean	2014	2015	2016	2017	Mean	2014	2015	2016	2017	2014	2015	2016	2017	2014	2015	2016	2017	2014	2015	2016	2017
UMC	0.475	0.488	0.436	0.492	0.473	0.988	0.930	0.909	1.000	0.957	0.907	0.855	0.835	0.928	0.826	0.780	0.764	0.856	0.744	0.704	0.694	0.784	0.663	0.635	0.623	0.712
DELTA	0.903	0.545	0.484	0.443	0.594	0.441	0.405	0.417	0.432	0.424	0.416	0.382	0.392	0.405	0.392	0.359	0.367	0.378	0.375	0.336	0.342	0.351	0.451	0.347	0.331	0.327
TSMC	0.052	0.715	0.056	0.705	0.382	0.792	0.843	0.861	1.000	0.874	0.717	0.781	0.780	0.923	0.642	0.719	0.700	0.847	0.567	0.657	0.619	0.770	0.492	0.595	0.539	0.693
MIC	0.369	0.417	0.994	1.000	0.695	0.667	0.647	0.561	0.526	0.600	0.629	0.623	0.590	0.573	0.592	0.599	0.619	0.621	0.560	0.575	0.648	0.668	0.533	0.551	0.677	0.715
WEC	0.561	0.565	0.580	0.553	0.565	0.329	0.368	0.347	0.360	0.351	0.340	0.374	0.355	0.365	0.351	0.380	0.363	0.371	0.361	0.385	0.371	0.378	0.376	0.393	0.384	0.386
TC	0.426	0.404	0.396	0.328	0.389	0.063	0.055	0.061	0.055	0.058	0.072	0.067	0.070	0.064	0.111	0.104	0.104	0.091	0.151	0.142	0.140	0.120	0.190	0.179	0.177	0.150
NTC	0.961	0.790	0.673	0.722	0.787	0.348	0.393	0.440	0.477	0.415	0.388	0.420	0.454	0.493	0.428	0.447	0.469	0.510	0.468	0.474	0.483	0.526	0.508	0.501	0.497	0.542
EM	1.000	1.000	0.994	1.000	0.998	0.015	0.017	0.018	0.016	0.017	0.114	0.109	0.110	0.114	0.212	0.206	0.207	0.213	0.311	0.304	0.305	0.311	0.409	0.403	0.404	0.410
GETI	1.000	0.939	1.000	1.000	0.985	1.000	0.882	0.871	0.989	0.935	1.000	0.886	0.884	0.983	1.000	0.891	0.897	0.978	1.000	0.897	0.910	0.973	1.000	0.903	0.923	0.967
FSTC	1.000	0.996	1.000	1.000	0.999	0.989	1.000	0.965	0.922	0.969	0.990	0.997	0.968	0.930	0.991	0.993	0.972	0.938	0.992	0.990	0.975	0.946	0.994	0.987	0.979	0.953
NTC	0.992	0.997	1.000	1.000	0.997	0.345	0.303	0.274	0.248	0.292	0.407	0.372	0.346	0.323	0.469	0.441	0.419	0.398	0.530	0.511	0.492	0.474	0.592	0.580	0.564	0.549
VTSC	0.950	0.998	1.000	0.992	0.985	0.619	0.964	0.884	1.000	0.867	0.638	0.954	0.887	0.999	0.665	0.947	0.899	0.998	0.698	0.953	0.912	0.997	0.732	0.960	0.924	0.997
SASPI	0.991	0.923	0.764	0.999	0.919	0.322	0.315	0.337	0.224	0.300	0.377	0.359	0.379	0.286	0.432	0.403	0.421	0.366	0.496	0.455	0.463	0.445	0.567	0.515	0.506	0.524
CTC	0.759	0.664	0.667	0.713	0.701	0.378	0.407	0.409	0.388	0.396	0.410	0.427	0.428	0.411	0.441	0.446	0.448	0.435	0.472	0.466	0.467	0.459	0.504	0.486	0.488	0.486
WWC	0.877	0.976	0.995	0.960	0.952	0.983	0.955	1.000	1.000	0.984	0.929	0.904	0.951	0.987	0.895	0.856	0.902	0.974	0.882	0.853	0.901	0.960	0.868	0.854	0.901	0.947
Mean	0.754	0.761	0.736	0.794	0.761	0.552	0.566	0.557	0.576	0.563	0.556	0.567	0.562	0.586	0.563	0.571	0.570	0.598	0.574	0.580	0.581	0.611	0.592	0.593	0.594	0.624

DMU	OERR																							
	alpha = 5				alpha = 6				alpha = 7				alpha = 8				alpha = 9				mean			
	2014	2015	2016	2017	2014	2015	2016	2017	2014	2015	2016	2017	2014	2015	2016	2017	2014	2015	2016	2017	2014	2015	2016	2017
UMC	0.582	0.575	0.562	0.640	0.520	0.518	0.502	0.568	0.484	0.487	0.448	0.504	0.481	0.487	0.444	0.500	0.478	0.488	0.440	0.496	0.632	0.614	0.590	0.666
DELTA	0.526	0.380	0.357	0.346	0.602	0.413	0.382	0.366	0.677	0.446	0.408	0.385	0.752	0.479	0.433	0.404	0.828	0.512	0.459	0.424	0.558	0.406	0.386	0.376
TSMC	0.417	0.532	0.458	0.617	0.343	0.526	0.378	0.540	0.271	0.573	0.298	0.578	0.198	0.620	0.217	0.620	0.125	0.668	0.137	0.663	0.419	0.630	0.458	0.694
MIC	0.505	0.528	0.711	0.763	0.478	0.505	0.745	0.810	0.451	0.483	0.779	0.858	0.424	0.461	0.835	0.905	0.397	0.439	0.915	0.953	0.508	0.529	0.724	0.763
WEC	0.401	0.413	0.411	0.404	0.429	0.442	0.444	0.427	0.462	0.473	0.477	0.458	0.495	0.504	0.511	0.488	0.528	0.534	0.546	0.520	0.416	0.433	0.429	0.422
TC	0.229	0.217	0.214	0.180	0.269	0.254	0.250	0.209	0.308	0.292	0.287	0.239	0.347	0.329	0.323	0.269	0.387	0.366	0.360	0.299	0.229	0.217	0.214	0.180
NTC	0.582	0.528	0.511	0.558	0.658	0.573	0.526	0.574	0.733	0.627	0.558	0.591	0.809	0.681	0.596	0.633	0.885	0.735	0.635	0.678	0.607	0.554	0.525	0.567
EM	0.508	0.503	0.502	0.508	0.606	0.602	0.601	0.606	0.705	0.702	0.699	0.705	0.803	0.801	0.797	0.803	0.902	0.900	0.896	0.902	0.508	0.503	0.502	0.508
GETI	1.000	0.909	0.936	0.970	1.000	0.915	0.948	0.976	1.000	0.921	0.961	0.982	1.000	0.927	0.974	0.988	1.000	0.933	0.987	0.994	1.000	0.909	0.936	0.979
FSTC	0.995	0.984	0.982	0.961	0.996	0.980	0.986	0.969	0.997	0.977	0.989	0.977	0.998	0.974	0.993	0.984	0.999	0.971	0.996	0.992	0.995	0.984	0.982	0.961
NTC	0.654	0.650	0.637	0.624	0.716	0.719	0.709	0.699	0.778	0.788	0.782	0.774	0.846	0.858	0.855	0.850	0.919	0.927	0.927	0.925	0.657	0.650	0.637	0.624
VTSC	0.766	0.966	0.936	0.996	0.801	0.973	0.949	0.995	0.836	0.979	0.961	0.994	0.872	0.985	0.974	0.993	0.911	0.992	0.986	0.992	0.769	0.968	0.936	0.996
SASPI	0.637	0.575	0.549	0.603	0.708	0.642	0.592	0.682	0.779	0.712	0.635	0.762	0.849	0.782	0.678	0.841	0.920	0.852	0.721	0.920	0.641	0.588	0.549	0.603
CTC	0.542	0.509	0.515	0.517	0.581	0.536	0.542	0.549	0.620	0.563	0.570	0.589	0.663	0.591	0.599	0.630	0.711	0.628	0.633	0.672	0.549	0.517	0.521	0.528
WWC	0.855	0.855	0.900	0.934	0.841	0.856	0.899	0.921	0.828	0.858	0.899	0.908	0.816	0.862	0.901	0.894	0.833	0.909	0.944	0.905	0.861	0.867	0.911	0.937
Mean	0.613	0.608	0.612	0.641	0.637	0.630	0.630	0.660	0.662	0.659	0.650	0.687	0.690	0.689	0.675	0.720	0.721	0.724	0.705	0.755	0.623	0.625	0.620	0.654

Note: "OERR", "FERR", and "SERR" denote overall efficiency score, first-stage efficiency score, and second-stage efficiency score, respectively.

5. Conclusions

This paper contributes to the literature on semiconductor industry efficiency by introducing a new hybrid model that combines AHP and two-stage additive network DEA to estimate sustainability efficiency in the presence of multiple undesirable outputs. This method makes up the disadvantage in weighting technique used additive decomposition approach to the two-stage network could bias toward the second stage. Through our modeling framework, we are able to ascertain whether overall inefficiency results from the inefficiency of an individual stage-level process, an internal resource imbalance, or both. The findings herein provide more insights and new information on semiconductor industry performance and management practices.

Consider just efficiency decomposition is one explicit limitation of traditional DEA models in regard to how to decide the appropriate weight of the network structure. To overcome the gap in the literature between overall efficiency and stage efficiencies under varying weights, this study uses AHP of the MCDM method to identify the "optimal" weights for the two-stage performance. The relative importance weights from a set of criteria via pairwise comparisons are 0.575 in the business growth stage and 0.425 in the energy utilization stage. Thus, we are able to identify semiconductor companies that operate below peer performance by incorporating the financial and ecological aspects of sustainability.

Taiwan's semiconductor manufacturing sector has exhibited a steady increase in its overall trend of sustainability performance. The integration of environmental impacts, as undesirable outputs, has been considered in various environmental efficiency assessments. The differences reflect that the level of undesirable output has a great influence on the sustainable development of semiconductor companies. According to the stage-level performance results, the performance of business growth is better than energy utilization; thus, the changing trend of overall sustainability performance is through a steady increase from environmental efficiency and not from economic efficiency. On the other hand, these individual-level efficiency scores provide insight into how the impacts which are derived from business growth or energy utilization are generated in the semiconductor industry.

From the policy and management perspective, the results of this study are compared with the results of the traditional DEA model. However, the semiconductor manufacturing sector may be overestimating its performance in the development of environmental protection through the traditional DEA model. Therefore, our new hybrid model allows the TMT of semiconductor firms to scrupulously identify whether changes in their firm's environmental pollution are driven by changes in effluent drainage, wastes, and/or greenhouse gas emissions. One interesting direction for future research would be to add the Economic Input-Output Life Cycle Assessment (EIO-LCA) into the analysis for examining a company's sustainability. Another one is the evaluation the social efficiency to measure the ability of a company to convert its produced wealth into the quality of life. Moreover, the model can take into consideration the weights of inputs or outputs.

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