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Environmental and economic performance of a biodiesel plant using waste cooking oil

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A B S T R A C T

This paper evaluates the environmental and economic performance of a biodiesel plant by using the data envelopment analysis framework considering two outputs (biodiesel and glycerin as a by-product of the biodiesel) and five inputs (waste cooking oil, methanol (MeOH), potassium hydroxide (KOH), power consumption used for operating the biodiesel plant, and truck diesel fuel used for the collection of waste cooking oil). From the results estimated using the time series database on monthly biodiesel production during August 2010 to March 2013, we found that there were many technologically inefficient production activities during the study period. We also demonstrate that a reduction of input costs for the study period of about 5% is possible and life-cycle CO_2 emissions associated with biodiesel productions can be further reduced, while the "first best" production activity in both cases of including and excluding external costs for life-cycle CO_2 emissions associated with biodiesel productions occurred in February 2013 and the minimum unit production cost was attained in this month.

1. Introduction

Biodiesel is one of the biomass fuels for diesel engines produced from vegetable or animal fat-based oil. Biodiesel has the following four advantages: carbon neutrality, potential for sustainable production, positive contribution to the energy self-sufficiency rate, and prevention of air pollution (Matsumura, 2006). The Japanese Ministry of the Environment published a report titled "The Vision for Reducing Greenhouse Gas Emissions by 80% by 2050" in August 2009 (Ministry of the Environment, 2009). According to the report, the Japanese government is attempting to increase the percentage of freight vehicles using biodiesel among all freight vehicles in Japan to 80%. Thus, we expect biodiesel demand to grow rapidly in the future. The Worldwatch Institute also reported that, by 2005, the production of biodiesel fuels in the E.U. states accounted for 89% of total global production (Worldwatch Institute, 2006; Kagawa et al., 2013).

However, as mentioned in Kagawa et al. (2013), most biodiesel plants in Japan have difficulty making a profit and need to depend on subsidies from their local governments. Therefore, it is necessary to raise the efficiency of their plant activities. Silalertruksa et al. (2012) conducted life-cycle costing analysis of palm oil biodiesel productions and they evaluated the cost performance depending on the portion of palm biodiesel blended with conventional diesel. However, Silalertruksa et al. (2012) did not clarify how the minimum production cost can be attained by reference biodiesel production activities. Kagawa et al. (2013) analyzed the productive efficiency of a biodiesel plant producing and selling biodiesel in the city of Kurume, Fukuoka, Japan and evaluated efficiency scores and potential cost reductions of the biodiesel plant using data envelopment analysis (DEA) (e.g., Färe et al., 1989, 1994, 1996; Tyteca, 1996). Since they did not consider environmental externalities directly and indirectly induced through product supply chains (i.e., life-cycle CO_2 emissions associated with biodiesel production), their result on an economically efficient activity may not minimize environmental external costs associated with the life-cycle CO_2 emissions.

Our DEA framework considers two outputs (biodiesel and glycerin as a by-product of the biodiesel) and five inputs (waste cooking oil, methanol (MeOH), potassium hydroxide (KOH), power consumption used for operating the biodiesel plant, and truck diesel fuel used for the collection of waste cooking oil). From the results estimated using the time series database on monthly biodiesel production during August 2010 to March 2013, we demonstrate how a particular biodiesel plant can achieve efficient production while reducing life-cycle CO_2 emissions. In addition, we

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also show how much the biodiesel plant can reduce the production cost of biodiesel by improving its productive efficiency and which month was the “first best” production activity in case of including environmental external costs associated with life-cycle CO_2 emissions.

The rest of the paper is organized as follows: Section 2 formulates the methodology, Section 3 describes data sources and presents empirical results of efficiency scores and the discussion, and finally Section 4 concludes the paper.

2. Methodology

We employed DEA with constant returns to scale to analyze environmental and productive efficiency (e.g., Färe et al., 1989, 1994, 1996; Tyteca, 1996). As in Fukuyama et al. (2011), our DEA framework considers the life-cycle CO_2 emissions of biodiesel production and provides an analysis of how production can be improved during technologically inefficient months.

The DEA framework without considering life-cycle CO_2 emissions can be formulated as follows:

$$\begin{aligned}
&\min\ \theta\\
&\text{s.t.}\quad \theta\mathbf{x}_z - \mathbf{X}\boldsymbol{\lambda} - \mathbf{s}_z^x = \mathbf{0}\\
&-\mathbf{y}_z + \mathbf{Y}\boldsymbol{\lambda} - \mathbf{s}_z^y = \mathbf{0}\\
&s_{zi}^x(i = 1, 2, \ldots, m) \geq 0\\
&s_{zi}^y(i = 1, 2, \ldots, n) \geq 0\\
&\lambda_j(j = 1, 2, \ldots, l) \geq 0
\end{aligned} \tag{1}$$

where $\mathbf{x}_z = (x_{z,i})$ is the input vector representing the input of materials i ($i = 1, 2, \ldots, m$) in month z (target month) and $\mathbf{y}_z = (y_{z,k})$ is the output vector representing the output of products k ($k = 1, 2, \ldots, n$) in month z. $\mathbf{X} = (x_{ij})$ and $\mathbf{Y} = (y_{kj})$ denote the input matrix representing the input amounts of materials i in months j ($j = 1, 2, \ldots, l$) and the output matrix representing the output amounts of products k in months j, respectively. $\boldsymbol{\lambda}=(\lambda_j)$ is the endogenously determined activity weight of months j. $\mathbf{s}_z^x$ and $\mathbf{s}_z^y$ are the slack vectors of material inputs and product outputs, respectively (e.g., Tone, 1993). In this study, the numbers of materials, products, and months are $m = 5$, $n = 2$, and $l = 32$, respectively.

Eq. (1) is the linear programming problem to seek, among production possibility sets, those production activities that would minimize the efficiency score θ while guaranteeing at least the target outputs. The production activity is efficient when $\theta = 1$ and inefficient when $\theta < 1$ (e.g., Färe et al., 1994).

Furthermore, we defined the following efficiency score τ taking into account the endogenously determined slacks on the material inputs and product outputs (Tsutsui, 2001; Fukuyama et al., 2011).

$$\tau = \theta - \frac{\bar{\mathbf{x}}_z \mathbf{s}_z^x + \bar{\mathbf{y}}_z \mathbf{s}_z^y}{m + n} \tag{2}$$

where

$$\bar{\mathbf{x}}_z = \left(\frac{1}{x_{1z}} \quad \frac{1}{x_{2z}} \quad \cdots \quad \frac{1}{x_{mz}}\right)$$

$$\bar{\mathbf{y}}_z = \left(\frac{1}{y_{1z}} \quad \frac{1}{y_{2z}} \quad \cdots \quad \frac{1}{y_{nz}}\right)$$

As related studies, Chen et al. (2006) and Liang et al. (2006) have proposed models for analyzing overall supply chain efficiency using supply chain DEA. Still, in order to use supply chain DEA, one must have access to detailed data on the inputs and outputs from upstream suppliers. The only data that we employed in this study were inputs and outputs in biodiesel production over the period from August 2010 to March 2013, supplied by Fuchigami Co., Ltd. We had insufficiently detailed data from upstream suppliers to be able to conduct supply chain DEA in this study.

3. Data and empirical results

This study focused on the production activity of a biodiesel plant operated by Fuchigami Co., Ltd. in the city of Kurume, Fukuoka, Japan and used monthly data on material inputs of waste cooking oil, methanol (MeOH), potassium hydroxide (KOH), power consumption used for operating activating the biodiesel plant, and truck diesel fuel used for the collection of waste cooking oil, and outputs of biodiesel and glycerin for August 2010 to March 2013 (32 months). We further estimated life-cycle CO_2 emissions associated with the biodiesel production by multiplying life-cycle CO_2 intensities (Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables by Nansai et al., 2012) by the inputs of those materials. The input–output data on biodiesel productions and the life-cycle CO_2 emissions are provided in Table 1. To be more specific, the life-cycle CO_2 emissions associated with “actual” material inputs at month z are estimated as follows.

$$b_z = \alpha_2 x_{z,2} + \alpha_3 x_{z,3} + \alpha_4 x_{z,4} + \alpha_5 x_{z,5} \tag{3}$$

where $x_{z,2}$, $x_{z,3}$, $x_{z,4}$, and $x_{z,5}$ represent physical inputs of KOH, MeOH, electrical power, and truck diesel fuel, respectively, and α_2, α_3, α_4, and α_5 represent life-cycle CO_2 intensities of KOH, MeOH, electrical power, and truck diesel fuel, respectively. Considering that KOH, MeOH, electrical power, and truck diesel fuel are classified into the soda chemicals sector, the methane derivative sector, the industrial electrical power sector, and petroleum products, respectively, in the Japanese Environmental Input-Output Table (Nansai et al., 2012), we used the life-cycle intensities of 19.03, 13.92, 27.34, and 5.51 t-CO_2/million yen given for soda chemicals, methane derivatives, electrical power, and petroleum products. The life-cycle intensities for monetary inputs were converted into those for physical inputs by using their purchase prices provided by Fuchigami Co., Ltd. Here it should be noted that the life-cycle CO_2 emissions associated with producing waste cooking oil as by-products are not considered due to the data limitation in this study.

In Table 1, B100 is 100% pure biodiesel and B5 is blended biodiesel (5% biodiesel and 95% petroleum diesel). For example, Fuchigami Co., Ltd. used only 1599 L of pure biodiesel in September 2010. In this month, the trucks used for the collection of waste cooking oil all employed 100% pure biodiesel fuel, and so the CO_2 emissions for the trucks were considered to be zero for September 2010 from the viewpoint of carbon neutrality. On the other hand, in August 2010, 549 L of B5 diesel and 930 L of B100 diesel (pure biodiesel) were used to collect waste cooking oil and therefore 521 L (=549 L × 0.95) of petroleum diesel were used to collect waste cooking oil. The life-cycle CO_2 emissions associated with using petroleum diesel were calculated by multiplying the amount of physical input by the life-cycle CO_2 intensity. Thus, the procedure used in this study was a hybrid life cycle analysis (LCA) (Suh and Huppes., 2005; Strømman et al., 2009; Acquaye et al., 2011). The system boundary is described in Fig. 1.

Table 1 shows how the biodiesel plant produces biodiesel as a primary product and glycerin as a by-product and emits CO_2 through the supply chains of biodiesel production. The maximum amount of biodiesel output during the study period is 39,360 L, in July 2012, and the month's inputs are 46,235 L of waste cooking oil, 758 kg of KOH, 8532 L of MeOH, 290 kWh of power, and 1492 L of truck diesel for collecting waste cooking oil. The life-cycle CO_2 emissions in July 2012 amount to 1.51 t-CO_2. Since the CO_2 emissions are associated with productions of biodiesel (i.e., primary