Identifying Environmentally-Important Industrial Clusters Using Multi-way Clustering Method

by

[*]Yuko OSHITA[†], Shigemi KAGAWA[†], Keisuke NANSAI[‡]

[†] Faculty of Economics, Kyushu University, Fukuoka, Japan

[‡] Research Center for Material Cycles and Waste Management, National Institute for Environmental Studies of Japan, Tsukuba, Japan

[*]Corresponding author:

Yuko OSHITA

Address for correspondence: Faculty of Economics, Kyushu University, 6-19-1 Hakozaki, Higashi-ku, Fukuoka, 812-8581, Japan, Phone and Fax: +81-92-642-2489, E-mail: oshita-yuko@live.jp

ABSTRACT

This paper combines input–output analysis with non-negative matrix factorization analysis widely used in the image segmentation and attempts to find the target industrial groups (industrial clusters) in Japan that have intensive CO_2 emissions. We generalized the industrial cluster analysis proposed by Kagawa *et al*. (2012) to identify environmentally-important industrial clusters from the entire economy. Furthermore, we estimated the optimal number of industry clusters using the Newman–Girvan modularity index. The empirical results obtained using the 2005 Input–Output Tables of Japan show that for example in automobile supply chain, the optimal number of industry clusters is 19, and 4 industry clusters are playing a key role in CO_2 emission reduction. We also found the CO_2 intensive clusters from the supply chains of other commodities and ranked the identified clusters on the basis of their within-cluster effects.

Keywords: CO_2, industry cluster, supply chain, multiway cut approach, nonnegative matrix factorization

1. Introduction

For climate change policies, Japanese government has proposed the “Sectoral Approaches” which are tools to reduce CO_2 emissions with a focus of CO_2 intensities of the particular sectors in question. However, the “Sectoral Approaches” do not afford an incentive to cooperate with other sectors on the carbon mitigations. In contrast, the “Cluster Approach” is clearly one of the alternatives. In the field of green supply-chain management, cooperation between industries within a supply chain is also recognized as an important approach to collectively reducing costs, energy consumption, and net environmental impacts (Simpson and Samson, 2008; Schliephake et al., 2009).

This paper attempts to analyze target industrial groups which can reduce CO_2 emissions effectively. To find the target industrial groups (industrial clusters), this paper combines input–output analysis (Miller and Blair, 2009) with non-negative matrix factorization analysis widely used in the image segmentation (e.g., Lee and Seung, 1999, 2001; Ding *et al*., 2005, 2008), which is useful in partitioning a network into sub-networks under a certain cut criterion and which detects industrial clusters in Japan that have intensive CO_2 emission.

To the best of our knowledge, Kagawa *et al*. (2012) is first attempt to identify environmentally-important industrial clusters by combining input-output analysis with non-negative matrix factorization analysis. This paper generalized the industrial cluster analysis proposed by Kagawa *et al*. (2012) and determined the optimal number of clusters using the Newman–Girvan modularity index (Newman and Girvan, 2004). Finally, this paper applies the network partition approach to the economic input–output table to find environmentally important groups of industries from the inter-industry networks. We demonstrate the usefulness of the method using a case study that identified CO_2-intensive industry clusters in the Japanese supply chain associated with various final commodities. Moreover we ranked the identified clusters on the basis of their within-cluster effects.

This paper is organized as follows: Section 1 describes the background, Section 2 generalizes the industrial cluster analysis proposed by Kagawa *et al*. (2012), Section 3 illustrates the data construction, Section 4 presents a case study, and Section 5 concludes the paper.

2. Methodology

2.1. Simplified input–output approach

We first replicate the industrial cluster analysis proposed by Kagawa *et al*. (2012) and generalized the cluster method. We start with the inter-industry delivery matrix, $\mathbf{Z} = (z_{ij})$ $(i, j = 1, \ldots, n)$, representing the input of a commodity from industry *i* to industry *j* (Miller and Blair, 2009), where *n* is the number of industries. It should be noted that the flow is ordinarily expressed in monetary units (e.g., US dollars). If the output vector showing the output of industry *j* is defined as $\mathbf{x} = (x_j)$, the input coefficient matrix can be obtained by $\mathbf{A} = (a_{ij}) = (z_{ij}/x_j)$ $(i, j = 1, \ldots, n)$. a_{ij} denotes the input from industry *i* necessary for producing a unit of output of industry *j*.

Here, let us suppose that final consumers such as households buy a commodity produced by the j_0th industry. Then we can define the final demand on the j_0th industry as f_{j_0} and the $(n \times 1)$ final demand as $\mathbf{f}_{j_0}$, where the element associated with the j_0th industry is f_{j_0} and all other elements are zero. Since the j_0th industry produces exactly the amount of the final demand, f_{j_0}, the output of the industry is straightforwardly estimated as f_{j_0} or, alternately, $\mathrm{diag}(\mathbf{f}_{j_0})$, the diagonalization of vector $\mathbf{f}_{j_0}$, for which only the (j_0, j_0) element of the matrix is non-zero. The j_0th industry requires materials and parts in order to produce the final demand $\mathbf{f}_{j_0}$. The inputs purchased by the j_0th industry can be estimated as $\mathbf{A}\mathrm{diag}(\mathbf{f}_{j_0})$. Since the materials and parts are also produced by using other materials and parts, we can similarly estimate the amount of inputs required for producing the demand for these materials and parts as $\mathbf{A}\mathrm{diag}(\mathbf{A}\mathbf{f}_{j_0})$.

Finally, we have the following input–output model (Ozaki, 1980; Suh, 2005; Nakamura *et al.*, 2011).

$$\mathbf{B}^{j_0} = \mathrm{diag}\left(\mathbf{f}^{j_0}\right) + \mathbf{A}\mathrm{diag}\left(\mathbf{f}^{j_0}\right) + \mathbf{A}\mathrm{diag}\left(\mathbf{A}\mathbf{f}^{j_0}\right) \tag{1}$$

The matrix $\mathbf{B}^{j_0} = (b_{ij}^{j_0})$ shown in eq. (1) can be regarded as a weighted directed graph showing the input from industry *i*, which was purchased to produce a commodity of industry *j*, required for the j_0th industry to produce the final demand for its good.

If the industrial CO_2 emission factor representing the CO_2 emission per unit of output of industry i is defined as vector $\boldsymbol{\alpha} = (\alpha_i)$, the CO_2 emissions directly induced by the inter-industry deliveries from industry i to industry j associated with the final demand on the j_0th industry can be formulated as the following matrix:

$$\mathbf{G}^{j_0} = \text{diag}(\boldsymbol{\alpha})\mathbf{B}^{j_0} = \text{diag}(\boldsymbol{\alpha})\text{diag}\left(\mathbf{f}^{j_0}\right) + \text{diag}(\boldsymbol{\alpha})\mathbf{A}\text{diag}\left(\mathbf{f}^{j_0}\right) + \text{diag}(\boldsymbol{\alpha})\mathbf{A}\text{diag}\left(\mathbf{A}\mathbf{f}^{j_0}\right) \qquad (2)$$

The graph $G = (V, E)$ can be derived from $\mathbf{G}^{j_0} = (g_{ij}^{j_0})$ such that the set of vertices is $V = \{1, \ldots, n\}$, the set of directed edges is $E = \left\{(i, j) \mid g_{ij}^{j_0} > 0\right\}$, and the weight assigned to edge (i, j) is $g_{ij}^{j_0}$.

2.2. Strength of relations matrix

In this study, we consider the CO_2 emissions associated with the inter-industrial flow between industry i and industry j. More specifically, we used the symmetric adjacency matrix $\mathbf{G}^{j_0*} = \left(g_{ij}^{j_0*}\right)$ $(i, j = 1, \ldots, n)$ (strength of relations matrix hereinafter), which can be derived from $\mathbf{G}^{j_0}$ as follows:

$$\begin{cases} g_{ij}^{j_0*} = g_{ij}^{j_0} + g_{ij}^{j_0} & (i \neq j) \\ g_{ij}^{j_0*} = 0 & (i = j) \end{cases} \qquad (3)$$

The strength of the relations matrix $\mathbf{G}^{j_0*}$ represents the strength of the CO_2 emissions associated with input exchanges between industries. In addition, the method presented here can be applied to any factor input, including energy, water, and land.

2.3. Network partition approach

Following previous studies (Shi and Malik, 2000; von Luxburg, 2007; von Luxburg *et al.*, 2008; Zhang and Jordan, 2008), the clustering problem is designed to find exhaustive and mutually exclusive K subsets, ⌋ = $\{C_1, C_2, \ldots, C_K\}$, such that not only total amount of CO_2 emission intensiveness of industrial relations between different groups is minimized, while the total amount of the within-group CO_2 intensity is maximized. This combinatorial optimization problem can be formulated as follows:

$$\begin{aligned} &\text{Minimize} \quad Ncut = \sum_{k=1}^{K} \frac{Cut(C_k)}{\sum_{u \in C_k} d_u} \\ &\text{subject to} \quad \cup_{k=1}^{K} C_k = V,\, C_k \cap C_l = \varnothing \left(k \neq l; k, l = 1, \ldots, K\right) \end{aligned} \tag{4}$$

where $Cut\left(C_k\right) = \sum_{u \in C_k} \sum_{v \notin C_k} g_{uv}^{j_0 *}$ (i.e., the numerator in eq. (4)) is the cut value giving the CO_2 emission intensity of the industrial relations between industrial group C_k and the rest of the industrial network and $d_u = \sum_{v \in V} g_{uv}^{j_0 *}$ in eq. (4) represents the weighted degree of each industrial sector u. The objective function of eq. (4) is frequently referred to as a normalized cut value (Ncut value).

Noting that the cut value can also be formulated as $Cut\left(C_k\right) = \sum_{u \in C_k} \sum_{v \in V} g_{uv}^{j_0 *} - \sum_{u \in C_k} \sum_{v \in C_k} g_{uv}^{j_0 *}$

$= \sum_{u \in C_k} d_u^{j_0} - \sum_{u \in C_k} \sum_{v \in C_k} g_{uv}^{j_0 *}$, eq. (4) can be rewritten using the following matrix notation (Zhang and Jordan, 2008):

$$\begin{aligned} &\text{Minimize} \quad Ncut = \mathrm{Tr}\left\{ \mathbf{H}' \left(\mathbf{D}^{j_0} - \mathbf{G}^{j_0 *} \right) \mathbf{H} \left(\mathbf{H}' \mathbf{D}^{j_0} \mathbf{H} \right)^{-1} \right\} \\ &\text{subject to} \quad \mathbf{H} \mathbf{1}_k = \mathbf{1}_n, \mathbf{H} \in \{0,1\}^{n \times K} \end{aligned} \tag{5}$$

where $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_n]'$ denotes the indicator matrix with the binary indicator vector $\mathbf{h}_i \in \{0,1\}^{K \times 1}$ for industry *i*, Tr represents the matrix trace operator, $\mathbf{D}^{j_0}$ the diagonal matrix whose diagonal elements are weighted degrees $d_u^{j_0}$, $\mathbf{1}_k$ the $(k \times 1)$ vector of ones, $\mathbf{1}_n$ the $(n \times 1)$ vector of ones, and the prime represents the matrix transpose operator. The matrix $\mathbf{D}^{j_0} - \mathbf{G}^{j_0 *}$ is often referred to as the Laplacian matrix[1] and is normally denoted by $\mathbf{L}^{j_0} \left(j_0 = 1, 2, \cdots, n \right)$ in spectral graph theory. An important point is that the combinatorial optimization problem in eq. (5) is an NP-complete problem.

One method for solving eq. (5) is to relax the indicator matrix **H** to take on real values, by which the combinatorial optimization problem is transformed into a generalized eigenvalue problem (Shi and Malik, 2000; von Luxburg, 2007; von Luxburg *et al*., 2008; Zhang and Jordan, 2008). This generalized eigenvalue problem is also known as the spectral relaxation of the original problem. However, switching to the spectral relaxation immediately implies that we are ignoring the nonnegativity constraints on the indicator matrix **H**. Therefore, as pointed in Ding *et al*. (2008), we cannot verify that the solutions of the generalized eigenvalue

[1] See e.g., Fiedler (1973) for the property for the Laplacian matrix.

problem bring about the best partitions of the network.

Considering this important methodological problem, in the present study, we employed another approach, the multiway cut approach using nonnegative matrix factorization, recently proposed by Ding *et al*. (2005). A corollary for the relationship between eq. (5) and nonnegative matrix factorization (Lee and Seung, 1999, 2001) as widely used in information technology applications is presented as follows.

Corollary (Ding *et al*., 2005).

The optimization problem in eq. (5) is equivalent to the following nonnegative matrix factorization problem (NMF problem):

$$\underset{\mathbf{H}\geq\mathbf{0}}{\text{Minimize}} \quad J_1 = \left\| \left(\mathbf{D}^{j_0}\right)^{-1/2} \mathbf{G}^{j_0 *} \left(\mathbf{D}^{j_0}\right)^{-1/2} - \mathbf{H}\mathbf{H}' \right\|_F^2 \tag{6}$$

where $\|\bullet\|^2$ is the Frobenius norm[2].

As in Lee and Seung (1999, 2001), the optimal solution of the matrix $\mathbf{H} = \left(h_{ij}\right)$ can be easily obtained by the following update rule (Ding *et al*., 2005):

$$h_{ij} \leftarrow h_{ij} \left(1 - \beta + \beta \frac{\left\{ \left(\mathbf{D}^{j_0}\right)^{-1/2} \mathbf{G}^{j_0 *} \left(\mathbf{D}^{j_0}\right)^{-1/2} \mathbf{H} \right\}_{ij}}{\left(\mathbf{H}\mathbf{H}'\mathbf{H}\right)_{ij}} \right) \tag{7}$$

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[2] The Frobenius norm of a square matrix **A** of order *n* is defined as $\|\mathbf{A}\|_F^2 = \sum_{j=1}^{n}\sum_{i=1}^{n} a_{ij}^2$.

where $0 < \beta \leq 1$. Following Ding *et al.* (2008), we set as $\beta = 0.5$ and the initial matrix $\mathbf{H}_0$ was obtained by the following equation, $\mathbf{H}_0 = \mathbf{E} + 0.2\mathbf{J}$ where $\mathbf{E} \in \{0,1\}^{n \times K}$ is the $(n \times K)$ indicator matrix approximated by the spectral clustering with *K*-means method (see Zhang and Jordan (2008) for the spectral clustering with *K*-means method) and $\mathbf{J}$ is the $(n \times K)$ matrix of ones. Iterative updating yields the matrix $\hat{\mathbf{H}} = (\hat{h}_{ij})$, which is an approximated indicator matrix with nonnegative values. The $(K \times 1)$ vector $\hat{\mathbf{h}}_i (1,\ldots,n)$ in the estimated indicator matrix $\hat{\mathbf{H}}$ can be regarded as a feature vector of vertex *i* (i.e., industrial sector *i*). Applying the *K*-means method to the data matrix $\hat{\mathbf{H}}$, we finally find *K* sets (clusters) such that the objective function $J_2 = \sum_{k=1}^{K} \sum_{i \in C_k} \left\| \hat{\mathbf{h}}_i - \mathbf{m}_k \right\|^2$ with the cluster center $\mathbf{m}_k = \frac{1}{|C_k|} \sum_{i \in C_k} \hat{\mathbf{h}}_i$ is minimized. Here, $|C_k|$ is the number of industrial sectors belonging to the *k*th cluster. Since initial cluster centers are randomly selected in the *K*-means method, different random initializations yield different cluster assignments. In order to find the best partition of the network, we obtained potential cluster assignments $\rfloor^{j_0\#} = \{C_1^{j_0\#}, C_2^{j_0\#}, \ldots, C_K^{j_0\#}\}$ by using the *K*-means algorithm *M* times and computed the normalized cut value under each cluster assignment. We chose an optimal cluster assignment $\rfloor^{j_0,opt} = \{C_1^{j_0,opt}, C_2^{j_0,opt}, \ldots, C_K^{j_0,opt}\}$ from the *M* results such that the computed normalized cut value is minimized.

2.4. Determining the number of clusters

Using the above multiway cut approach, we can find the optimal cluster assignment for any number of clusters, K. However, an important problem is that the multiway cut approach is silent about determining the number of clusters. For this methodological problem, Newman and Girvan (2004) developed a useful index, the modularity index, to determine the plausible number of clusters detected in the network partition analysis. The modularity index for any K clusters can be formulated as follows:

$$Q^{j_0}(K)=\sum_{k=1}^{K}\left\{\frac{\sum_{i\in C_k^{j_0,opt}}\sum_{j\in C_k^{j_0,opt}} g_{ij}^{j_0*}}{\sum_{i=1}^{n}\sum_{j=1}^{n} g_{ij}^{j_0*}}-\left(\frac{\sum_{i\in C_k^{j_0,opt}}\sum_{j\in V} g_{ij}^{j_0*}}{\sum_{i=1}^{n}\sum_{j=1}^{n} g_{ij}^{j_0*}}\right)^2\right\}=\sum_{k=1}^{K}\left\{p_{kk}^{j_0}-\left(q_k^{j_0}\right)^2\right\} \tag{8}$$

where $p_{kk}^{j_0}$ represents the within-cluster ratio for the kth cluster and $q_k^{j_0}$ represents the betweenness ratio for the kth cluster. An important point is that the best cluster assignment should maximize the modularity index such that the within-cluster ratio is high and the betweenness ratio is low. In practice, Newman and Girvan (2004) and Newman (2004) demonstrated that the highest Q^{j_0} value indicates well-separated clusters. In the present study, we use the modularity index to determine the optimal number of clusters, $K^{j_0,opt}$. Here it should noted that the within-cluster effect representing the total CO_2 emission within a cluster is formulated as $\sum_{i\in C_k^{j_0,opt}}\sum_{j\in C_k^{j_0,opt}} g_{ij}^{j_0*}$. Finally, we identified the most CO_2-intensive cluster $C_k^{j_0,opt}$ and its relevant final commodity j_0 in the entire economy such that the within-cluster effect is maximized as follows.

$$\left(C_k^{j_0,opt}, j_0\right)\in \arg\max \sum_{i\in C_k^{j_0,opt}}\sum_{j\in C_k^{j_0,opt}} g_{ij}^{j_0*} \tag{9}$$

3. Preparation of basic data

We examined industrial CO_2 emissions in tons CO_2 induced by production activities of the Japanese industries. As source data, we used the Japanese Benchmark Input–Output Table for the producer prices in 2005 (393 commodity sectors) provided by the Ministry of Internal Affairs and Communications of Japan and the greenhouse gas emission (GHG) database provided by the National Institute for Environmental Studies of Japan (Nansai *et al.*, 2007, 2009). For the analysis, the CO_2 emissions from the combustion of primary and secondary energy resources in Table A are considered.

From the GHG database, the total CO_2 emissions of each sector was calculated by summing up CO_2 emissions associated with the energy inputs. The CO_2 emission coefficient of industry *i*, denoted α_i, was then obtained by dividing the industrial emissions by the quantity of industrial production. Finally, we obtained the diagonal matrix with industrial emissions and constructed the (393×393) adjacency matrix $\mathbf{G}^{j_0}\left(j_0 = 1, 2, \ldots, 393\right)$ by substituting the diagonal emission coefficient matrix $\mathrm{diag}(\boldsymbol{\alpha})$, the input coefficient matrix $\mathbf{A}$ from the benchmark input–output table, and the diagonalized matrix for the any commodity domestic final demand (i.e., household consumption expenditure of any final commodity + fixed capital formation of any final commodity + increase in stock of any final commodity) $\mathrm{diag}\left(\mathbf{f}^{j_0}\right)$ into the right-hand side of eq. (2). Furthermore, the symmetric adjacency matrix $\mathbf{G}^{j_0 *}$ was obtained using eq. (3) and then the degree matrix $\mathbf{D}^{j_0}$ was obtained from the (393×393) symmetric adjacency matrix.

4. Result and discussion

We found CO_2-intensive industrial clusters from the entire Japanese economy using the method explained in Section 2. Moreover we also ranked the identified clusters on the basis of their within-cluster effects. Finally, identifying environmentally-important industrial clusters in Japan, we suggested the policy to reduce the emissions and sustainable cooperation among different industries.

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