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Eco-design of transportation in sustainable supply chain management: A DEA-like method

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ABSTRACT

This study addresses the issue of eco-design for transportation in sustainable supply chain management (SSCM). Data envelopment analysis (DEA) is adopted and extended to construct a model for this application. This proposed model, together with the tractable algorithm developed in this research, can provide stakeholders with a Pareto Optimal transportation strategy. This derived transportation strategy can help stakeholders realize certain transportation goals with less resource consumption and pollution emission. The discussion presented leads to a heuristic Joint Transportation Policy and concludes with two useful suggestions for putting the strategy into practice. The proposed model was used in an empirical study of design sustainable transportation mechanism for one air-condition manufacturer in China to transport its products as well, the analysis further demonstrating the theoretical and practical value of this research.

Introduction

Sustainable supply chain management (SSCM) has received great attention from both academia and industry in the last decade after pioneering studies on operations management (OM) and environmental management (Corbett and Kleindorfer, 2003) and sustainability in OM (Corbett and Klassen, 2006). As Linton et al. (2007) pointed out, to achieve sustainability in supply chain management, environmentally friendly procedures should be used in each part of the supply chain, including product design, manufacturing, using, recycling, and transporting among suppliers, manufacturers, and customers. Knowing that transportation is one of the largest sources of environmental pollution in supply chains (Wu and Dunn, 1995), proper design of logistics systems will certainly have massive positive impacts in SSCM performance improvement (Elhedhli and Merrick, 2012). Thus addressing the issue of eco-design for transportation in SSCM should be quite significant in both theoretical and practical OM.

However, achieving a reasonable and valuable eco-design for transportation in SSCM can be challenging for the following reasons. First, to meet the essential aim of sustainability, the transportation eco-design should fully take into consideration a variety of social, economic, and environmental indicators: labor, profit, energy consumption, pollution, etc. (Krishnan, 2013). It is not sufficient to simply aggregate these factors, weighted exogenously or non-weighted, to derive a composite indicator for decision making because doing so can have an obvious detrimental bias in practice (Chen and Delmas, 2011). Because the real world conditions of SSCM are complex and dynamic (Bettencourt et al., 2007), both determining and combining preferences are difficult in such an environment (Baucells and Sarin, 2003). Moreover, some of these factors can conflict with

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each other as stakeholder characteristics and preferences shift dramatically in different contexts and times (Griffin, 2000). For all of these reasons, providing appropriate exogenous weights can be a formidable task.

Second, there exist both positive and negative factors in the process of transportation as related research has mentioned (Esters and Marinov, 2014; Song et al., 2014). Most negative factors, such as greenhouse gas emissions and toxic waste releases, do not have a well-established market from which we can obtain reliable cost signals (Chen, 2014). This means that prioritizing different environmental factors in terms of profit and energy consumption becomes difficult.

Numerous articles, including both theoretical and empirical studies, have used data envelopment analysis (DEA) to analyze transportation while incorporating environmental factors and thereby have shown that this famous non-parametric approach has a great ability to overcome the above two drawbacks (Cui and Li, 2014; Hampf and Krüger, 2014). DEA was firstly introduced by Charnes et al. (1978), and soon after this technique was popularized for use in a variety of fields: supply chain management (Liang et al., 2006), performance evaluation (Liang et al., 2008), resource allocation (Li et al., 2009), mechanism design (Sun et al., 2014), strategic management (Chen et al., 2015), etc. DEA does not need any a priori assumptions about weights, production functions, and probability distributions (Emrouznejad et al., 2008), and these solid strengths compared with other methods have led to numerous DEA-based theoretical and empirical articles dealing with environmental management and sustainable issues being contributed to the literature (Zhou et al., 2008; Song et al., 2012). Thus DEA can be considered as one of the most powerful tools in dealing with sustainability (Chen and Delmas, 2012).

Recently, several excellent works have been published which address environmentally friendly transportation and SSCM issues, works which have high correlation with our topic. Chang et al. (2014) developed an SBM-DEA model to analyze the environmental efficiency of transportation. Kumar et al. (2014) proposed a unified green DEA (GDEA) model to deal with pollution of suppliers as a dual-role factor to seek the best supplier in SSCM. Then Azadi et al. (2015) built a fuzzy DEA model to deal with the uncertainty in supplier selection in SSCM. All their works are admirable, but none of them discuss the scenario in which the decision maker needs to select multiple transporters. In this paper, we adopt and extend traditional DEA method to build a new model to help decision makers select multiple transporters simultaneously. With the proposed model, decision makers can be provided with a Pareto Optimal eco-design policy for transportation in SSCM. Via this policy, stakeholders can transport certain amounts of products using fewer resources and emitting less pollution.

The rest of this paper is organized as follows. Section 'Methodology description and modeling' contains the detailed methodology description and the development of the model. In some situations the normal solution technique is impractical for this model, so an alternative algorithm for solving the proposed model is developed in Section 'Solution method'. In Section 'Discussion and recommendations' there is further discussion of the results of the proposed model and some practical suggestions. An empirical study of design sustainable transportation mechanism for one air-condition manufacturer in China to transport its products is shown in Section 'Empirical study'. Conclusions and further extensions are summarized in Section 'Conclusion and extension'.

Methodology description and modeling

Preliminaries

Sustainability requires simultaneous realization of economic, environmental, and social goals, so we take various economic, environmental, and social indicators into account when doing eco-design of transportation in SSCM. These factors can be divided into two categories, positive and negative. Common sense dictates that one must maximize positive factors while minimizing the negative. In Chen and Delmas's research, they use a classical CCR model to characterize this features, treating positive indices as outputs and negative ones as inputs (Chen and Delmas, 2011). Their model is shown below.

$$\begin{aligned} Max \quad & \frac{\sum_{r=1}^{s} u_r y_{lr}}{\sum_{i=1}^{m} v_i x_{li}} \\ s.t. \quad & \frac{\sum_{r=1}^{s} u_r y_{jr}}{\sum_{i=1}^{m} v_i x_{ji}} \leqslant 1, \ for \ j = 1, \ldots, n, \\ & u_r \geqslant 0 \ for \ r = 1, \ldots, s; \\ & v_i \geqslant 0 \ for \ i = 1, \ldots, m. \end{aligned}$$

Treating positive indices as outputs and negative ones as inputs in sustainability issues is reasonable, and numerous empirical studies have already done this (Azadi et al., 2015). For example, Azadi et al. (2015) use the negative indices *eco-design cost* (environmental dimension) and *cost of work safety and labor health* (social dimension) as input in their empirical analysis. We will adopt this technique in our research as well. Further, in order to characterize the transportation process more accurately, we will consider as input the negative indices (e.g. social cost) which occur before transportation, and consider the post-transportation negative indices (e.g. environmental pollution) as undesirable outputs.

Model for eco-design of transportation in SSCM

We consider the transportation system in a supply chain that contains n homogeneous logistics companies and a single manufacturer. To transport its products to retailers, the manufacturer need to hire at least one logistics company. Since the manufacturer wants to optimize its SSCM performance, it wants to find a transportation strategy that transports a certain amount of products with less input use (like resource consumption and various costs) and also less undesirable output result (like pollution emission).

We use LC_j to represent the jth logistics company, $j = 1, \ldots, n$. We further assume that LC_j has n_j transportation tools. The capacity of per transportation tool is y_j. When used, each transportation tool has m kinds of input and s kinds of undesirable output. We then use x_{ij} and z_{rj} to represent the ith input and rth output of LC_j respectively, $i = 1, \ldots, m$ and $r = 1, \ldots, s$. Suppose the manufacturer has C products that need to be transported, and it chooses $\alpha_j (0 \leqslant \alpha_j \leqslant n_j, \alpha_j \in \mathbf{N})$ transportation tools from the jth logistics company. We then use γ to represent the combination of $\alpha_j (j = 1, \ldots, n)$, i.e. we have $\gamma = (\alpha_1, \ldots, \alpha_n)$. In order to avoid potential misunderstanding, for each α_j belongs to γ, we rewrite is as α_j^{γ}. Obviously, not all combinations of $\alpha_j (j = 1, \ldots, n)$ would be feasible schemes in the real world, so we use set E to represent the entirety of all feasible combinations of $\alpha_j (j = 1, \ldots, n)$, i.e. we have $E = \left\{ \gamma \middle| \sum_{j=1}^{n} \alpha_j^{\gamma} y_j \geqslant C, 0 \leqslant \alpha_j^{\gamma} \leqslant n_j, \alpha_j^{\gamma} \in \mathbf{N} \right\}$.

At this point, the description of primary notation is over. Readers may later find that the notation used in our research is quite different from the traditional notation in the DEA literature. In order to avoid potential misunderstanding, we present a brief clarification before doing model construction.

In our research the decision making units (DMUs) are not logistics companies but the feasible combinations of $\alpha_j (j = 1, \ldots, n)$. This is because our purpose in doing eco-design of transportation is to help the manufacturer select logistics companies to transport its products to retailers. Here we assume that the total amount of product, C, is constant, which means that the decision made by the manufacturer is from among all feasible combinations of these logistics companies that can satisfy the manufacturer's demand. Since E is the entirety of all feasible combinations, it is obvious that from the point of view of traditional DEA terminology, there are actually $|E|$ DMUs in our research. In other words, within each logistics company there are many possible combinations of transportation services and traditional DEA terminology would consider each combination to be a DMU. A traditional-view DMU corresponding to combination $\alpha_j^{\gamma} (j = 1, \ldots, n)$ has input, undesirable output, and desirable output denoted as $\sum_{j=1}^{n} a_j^{\gamma} x_{ij}, \sum_{j=1}^{n} a_j^{\gamma} z_{rj}$ and C respectively.

Then, according to the traditional theory of DEA, we can use the following model (1) to calculate the optimal eco-design of transportation strategy of the manufacturer.

$$
\begin{aligned}
\min \quad & \eta_{\gamma_0} = \frac{\sum_{i=1}^{m} v_i \left(\sum_{j=1}^{n} \alpha_j^{\gamma_0} x_{ij} \right) + \sum_{r=1}^{s} u_r \left(\sum_{j=1}^{n} \alpha_j^{\gamma_0} z_{rj} \right)}{wC} \\
s.t. \quad & \frac{\sum_{i=1}^{m} v_i \left(\sum_{j=1}^{n} \alpha_j^{\gamma} x_{ij} \right) + \sum_{r=1}^{s} u_r \left(\sum_{j=1}^{n} \alpha_j^{\gamma} z_{rj} \right)}{wC} \geqslant 1, \ for \ \gamma \in E \\
& \sum_{j=1}^{n} \alpha_j^{\gamma} y_j \geqslant C \\
& 0 \leqslant \alpha_j^{\gamma} \leqslant n_j \\
& v_i, u_r, w \geqslant \varepsilon > 0
\end{aligned}
\tag{1}
$$

Here $v_i, u_r, w \geqslant \varepsilon > 0$ are the variable weights to be determined by the solution of model (1). Model (1) is nonlinear, while we have following Theorem 1 to show that it can be converted to a linear one. The details of the transformation are contained in the proof of Theorem 1.

Theorem 1. *Model (1) can be convert to a linear model. Suppose there has $\eta_{\gamma^*} = 1$ for some $v_i, u_r, w \geqslant \varepsilon > 0$ and $\alpha_j^{\gamma^*} (\gamma^* \in E, j = 1, \ldots, n)$ in model (1). Then the desired eco-design of transportation in SSCM for the manufacturer is to hire $\alpha_j^{\gamma^*}$ transportation tools from the jth logistics company. This strategy is a Pareto Optimal one. Furthermore, if we denote $F = \left\{ \gamma \middle| \eta_{\gamma} = 1, \gamma \in E \right\}$, then F is non-empty unless E is empty.*

Proof of Theorem 1. For each fixed α_j^{γ}, if we denote $\sum_{j=1}^{n} \alpha_j^{\gamma} x_{ij}, \sum_{j=1}^{n} \alpha_j^{\gamma} z_{rj}$, and C as $x'_{i\gamma}, z'_{r\gamma}$, and y'_{γ} respectively, then model (1) can be translated into following model (2).

$$
\begin{aligned}
\min \quad & \eta_{\gamma_0} = \frac{\sum_{i=1}^{m} v_i x'_{i\gamma_0} + \sum_{r=1}^{s} u_r z'_{r\gamma_0}}{w y'_{\gamma_0}} \\
s.t. \quad & \frac{\sum_{i=1}^{m} v_i x'_{i\gamma} + \sum_{r=1}^{s} u_r z'_{r\gamma}}{w y'_{\gamma}} \geqslant 1, \ for \ \gamma \in E \\
& v_i, u_r, w \geqslant \varepsilon > 0
\end{aligned}
\tag{2}
$$

Then the optimization problem in model (1) turns into a standard DEA problem with $|E|$ DMUs, where each DMU_{γ} has m inputs, 1 desirable output, and s undesirable outputs. By denote the ith input, desirable output, and rth undesirable output as $x'_{i\gamma}, y'_{\gamma}$ and $z'_{r\gamma}$ respectively, model (1) is equivalent to model (2). Since model (2) can be convert to a linear model with standard C–C transformation, it can be concluded that model (1) can be convert to a linear model as well. In addition, since F will be non-empty if E is non-empty in model (2), thus we can prove the last part of the theorem.

Now let us use proof by contradiction to prove the second part of Theorem 1.

Suppose $\eta_{\gamma^*} = 1$ but $\left\{\alpha_j^{\gamma^*}\right\}$ $(j = 1, \ldots, n)$ is not Pareto Optimal. Then there must exist $\gamma \in E$, such that at least one of the inequalities in (3) below is strict.

$$\begin{aligned}
&\sum_{j=1}^{n} \alpha_j^{\gamma^*} x_{ij} \geqslant \sum_{j=1}^{n} \alpha_j^{\gamma} x_{ij},\ i = 1, \ldots, m \\
&\sum_{j=1}^{n} \alpha_j^{\gamma^*} z_{rj} \geqslant \sum_{j=1}^{n} \alpha_j^{\gamma} z_{rj},\ r = 1, \ldots, s
\end{aligned} \tag{3}$$

Then for any $v_i,\ u_r,\ w$ such that

$$\left(\sum_{i=1}^{m} v_i \sum_{j=1}^{n} \alpha_j^{\gamma^*} x_{ij} + \sum_{r=1}^{s} u_r \sum_{j=1}^{n} \alpha_j^{\gamma^*} z_{rj}\right) \bigg/ w \sum_{j=1}^{n} \alpha_j^{\gamma^*} y_j = 1,$$

that $v_i,\ u_r,\ w$, will no longer be a feasible solution of model (1). Because

$$1 = \left(\sum_{i=1}^{m} v_i \sum_{j=1}^{n} \alpha_j^{\gamma^*} x_{ij} + \sum_{r=1}^{s} u_r \sum_{j=1}^{n} \alpha_j^{\gamma^*} z_{rj}\right) \bigg/ w \sum_{j=1}^{n} \alpha_j^{\gamma^*} y_j > \left(\sum_{i=1}^{m} v_i \sum_{j=1}^{n} \alpha_j^{\gamma} x_{ij} + \sum_{r=1}^{s} u_r \sum_{j=1}^{n} \alpha_j^{\gamma} z_{rj}\right) \bigg/ w \sum_{j=1}^{n} \alpha_j^{\gamma} y_j$$

therefore we will have $\eta_{\gamma^*} > 1$, which is contradictory to the assumption. This completes the proof of Theorem 1. □

Solution method

Next, we come to the solution of model (1). Certainly, it is possible to list all elements contained in set E. Then the programming problem in model (1) will degenerate to a normal DEA problem which can be solved via conventional techniques. However, in the worst case, the number of $|E|$ could be equal to $\prod_{j=1}^{n} n_j$ which means that if n and n_j are sufficiently large, $|E|$ will be too huge to calculate the solution in normal ways. This is the motivation for developing an alternative approach to save calculation time.

Since the purpose of developing model (1) is to seek any one Pareto Optimal eco-design for transportation in SSCM, we naturally do not need to calculate the score of all potential transportation schemes as required in traditional DEA solution methods. Therefore, we propose the following model (4) to seek one of the Pareto Optimal strategies contained in set F.

$$\begin{aligned}
&\min \frac{1}{m} \sum_{i=1}^{m} \frac{\sum_{j=1}^{n} \alpha_j^{\gamma} x_{ij}}{\sum_{j=1}^{n} x_{ij}} + \frac{1}{r} \sum_{r=1}^{s} \frac{\sum_{j=1}^{n} \alpha_j^{\gamma} z_{rj}}{\sum_{j=1}^{n} z_{rj}} \\
&s.t.\ \gamma \in E
\end{aligned} \tag{4}$$

The validity of model (4) could be confirmed by Theorem 2 below.

Theorem 2. *Suppose* $\left\{\alpha_j^{\gamma^{**}}\right\}$ $(j = 1, \ldots, n)$ *is an optimal solution of model* (4). *Then* γ^{**} *belongs to set F. Thus hiring* $\alpha_j^{\gamma^{**}}$ *transportation tools from the jth logistics company is a Pareto eco-design for transportation in SSCM for that manufacturer.*

To prove Theorem 2, we have the following three lemmas.

Lemma 1. *Suppose* $\left\{\alpha_j^{\gamma^{**}}\right\}$ $(j = 1, \ldots, n)$ *is an optimal solution of model* (4). *Then we have* $\overline{\eta}_{\gamma^{**}} = 1$, *here* $\overline{\eta}_{\gamma}$ *is the objective function in model* (5) *below.*

$$\begin{aligned}
\min\quad & \overline{\eta}_{\gamma_0} = \frac{\sum_{i=1}^{m} v_i \left(\sum_{j=1}^{n} \left(\alpha_j^{\gamma_0} + 1\right) x_{ij}\right) + \sum_{r=1}^{s} u_r \left(\sum_{j=1}^{n} \left(\alpha_j^{\gamma_0} + 1\right) z_{rj}\right)}{w\left(C + \sum_{j=1}^{n} y_j\right)} \\
s.t.\quad & \frac{\sum_{i=1}^{m} v_i \left(\sum_{j=1}^{n} \left(\alpha_j^{\gamma} + 1\right) x_{ij}\right) + \sum_{r=1}^{s} u_r \left(\sum_{j=1}^{n} \left(\alpha_j^{\gamma} + 1\right) z_{rj}\right)}{w\left(C + \sum_{j=1}^{n} y_j\right)} \geqslant 1,\ for\ \gamma \in E \\
& \sum_{j=1}^{n} \alpha_j^{\gamma} y_j \geqslant C \\
& 0 \leqslant \alpha_j^{\gamma} \leqslant n_j \\
& v_i, u_r, w \geqslant \varepsilon > 0
\end{aligned} \tag{5}$$

Proof of Lemma 1. We use proof by contradiction here to prove Lemma 1. Suppose $\overline{\eta}_{\gamma^{**}} > 1$. Then $\left\{\sum_{j=1}^{n}\left(\alpha_j^{\gamma^{**}}+1\right)x_{ij}, C+\sum_{j=1}^{n}y_j, \sum_{j=1}^{n}\left(\alpha_j^{\gamma^{**}}+1\right)z_{uj}\right\}$ is not Pareto Optimal in model (5). Thus there exists $\gamma \in E$ such that at least one of the inequalities in (6) below is strict.

$$\begin{aligned}
&\sum_{j=1}^{n}\left(\alpha_j^{\gamma^{**}}+1\right)x_{ij} \geqslant \sum_{j=1}^{n}\left(\alpha_j^{\gamma}+1\right)x_{ij},\ i=1,\ldots,m\\
&C+\sum_{j=1}^{n}y_j \geqslant C+\sum_{j=1}^{n}y_j\\
&\sum_{j=1}^{n}\left(\alpha_j^{\gamma^{**}}+1\right)z_{rj} \geqslant \sum_{j=1}^{n}\left(\alpha_j^{\gamma}+1\right)z_{rj},\ r=1,\ldots,s
\end{aligned} \tag{6}$$

Then we have

$$\frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}x_{ij}}{\sum_{j=1}^{n}x_{ij}}+\frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}z_{rj}}{\sum_{j=1}^{n}z_{rj}}<\frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma^{**}}x_{ij}}{\sum_{j=1}^{n}x_{ij}}+\frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma^{**}}z_{rj}}{\sum_{j=1}^{n}z_{rj}}.$$

This implies that $\left\{\alpha_j^{\gamma^{**}}\right\}$ $(j=1,\ldots,n)$ is not an optimal solution of model (4), which is a contradiction. So we have $\overline{\eta}_{\gamma^{**}} = 1$. □

Before giving the next lemma, let us recall of the definition made by Chen and Delmas (2012), which is used to characterize the relationship between different feasible production plans. The details of that definition are as follows.

Definition 1 (Chen and Delmas (2012)). The production plan $(x_{om}, y_{on}, u_{op}) \in \Omega$ is nondominated in outputs if there does not exist any $\left(x_{om}, y'_{om}, u'_{op}\right) \in \Omega$ such that $\left(x_{om}, y'_{om}, u'_{op}\right) \neq (x_{om}, y_{on}, u_{op}) \in \Omega$ while $y'_{on} \geqslant y_{on}$ and $u'_{op} \geqslant u_{op}$. Otherwise, $(x_{om}, y_{on}, u_{op}) \in \Omega$ is dominated.

Chen and Delmas theoretically proved the equivalence between Pareto efficiency and nondomination in outputs. In our paper, we propose the following slight extension of Chen and Delmas's definition.

Definition 2. For $DMU_{j_1} \equiv \left(x_{ij_1}, y_{rj_1}, z_{uj_1}\right) \neq \left(x_{ij_2}, y_{rj_2}, z_{uj_2}\right) \equiv DMU_{j_2}$, we say DMU_{j_1} Pareto dominates DMU_{j_2} if we have $x_{ij_1} \leqslant x_{ij_2}, y_{rj_1} \geqslant y_{rj_2}$, and $z_{uj_1} \leqslant z_{uj_2}$ for every i, r, and u.

Lemma 2. *If DMU_{j_1} does not Pareto dominate DMU_{j_2}, then $DMU_{j_1}+DMU_j$ does not Pareto dominates $DMU_{j_2}+DMU_j$ either.*

Proof of Lemma 2. We use proof by contradiction here to prove Lemma 2. Suppose $DMU_{j_1}+DMU_j$ Pareto dominates $DMU_{j_2}+DMU_j$, then at least one of the inequalities in (7) below is strict.

$$\begin{aligned}
&x_{ij_1}+x_{ij} \leqslant x_{ij_2}+x_{ij},\ i=1,\ldots,m\\
&y_{j_1}+y_j \geqslant y_{j_2}+y_j\\
&z_{rj_1}+z_{rj} \leqslant z_{rj_2}+z_{rj},\ r=1,\ldots,s
\end{aligned} \tag{7}$$

Then at least one of the inequalities in (8) below is strict as well.

$$\begin{aligned}
&x_{ij_1} \leqslant x_{ij_2},\ i=1,\ldots,m\\
&y_{j_1} \geqslant y_{j_2}\\
&z_{rj_1} \leqslant z_{rj_2},\ r=1,\ldots,s
\end{aligned} \tag{8}$$

Thus we have that DMU_{j_1} Pareto dominates DMU_{j_2}, this is a contradiction. Then we have finished the proof of Lemma 2. □

Lemma 3. *One DMU is Pareto Optimal if and only if it does not be Pareto dominated by any other DMU.*

The proof of Lemma 3 is trivial, thus we omit it here. Then we come to prove Theorem 2.

Proof of Theorem 2. According to Lemma 1, if $\left\{\alpha_j^{\gamma^{**}}\right\}$ $(j=1,\ldots,n)$ is an optimal solution of model (4), then we have that $\left\{\sum_{j=1}^{n}\left(\alpha_j^{\gamma^{**}}+1\right)x_{ij}, C+\sum_{j=1}^{n}y_j, \sum_{j=1}^{n}\left(\alpha_j^{\gamma^{**}}+1\right)z_{uj}\right\}$ is Pareto Optimal for model (6). Then according to Lemmas 2 and 3, $\left\{\sum_{j=1}^{n}\left(\alpha_j^{\gamma^{**}}\right)x_{ij}, C, \sum_{j=1}^{n}\left(\alpha_j^{\gamma^{**}}\right)z_{uj}\right\}$ is Pareto Optimal for model (1). Then we have $\eta_{\gamma^{**}} = 1$, so γ^{**} belongs to set F. □.

Discussion and recommendations

With model (1) and model (4) proposed in Sections 'Methodology description and modeling' and 'Solution method' respectively, one can easily get a Pareto Optimal eco-design for transportation. Using this eco-design, the manufacturer could transport its products to retailers with less resource consumption and less pollution emission, and thus improve its performance in SSCM. However, there are still some points that need our attention.

According to model (1), there exist two constraints, $\sum_{j=1}^{n}\alpha_j^{\gamma}y_j \geqslant C$ and $0 \leqslant \alpha_j^{\gamma} \leqslant n_j, \alpha_j^{\gamma} \in N$. Since α_j^{γ} is nonnegative integer, then the inequality in $\sum_{j=1}^{n}\alpha_j^{\gamma}y_j \geqslant C$ will probably be strict when the optimal solution is achieved for model (1). This implies that even though the derived eco-design of transportation has been proved to be Pareto Optimal in both resource consumption and pollution emission, it does have some waste in terms of the transportation capacity. In order to make full use of the transportation capacity, we propose following Joint Transportation Policy in SSCM.

Joint transportation policy

Assume $\left\{\alpha_j^{\gamma^*}\right\}$ $(j = 1, \ldots, n)$ is a Pareto Optimal eco-design for transportation. If $\sum_{j=1}^{n}\alpha_j^{\gamma^*}y_j - C \neq 0$, the manufacturer should seek a suitable cooperator (another enterprise requiring transportation) to transport products together.

In fact, joint transportation is essentially the same as joint replenishment. Similar to joint replenishment, joint transportation can be proved to save costs and so it can be concluded that joint transportation has advantages in operations management. We then come to show that joint transportation also has advantages in environmental management.

Theorem 3. *Suppose* $\left\{\bar{\alpha}_j^{\gamma}\right\}$ $(j = 1, \ldots, n), \left\{\tilde{\alpha}_j^{\gamma}\right\}$ $(j = 1, \ldots, n)$ *and* $\left\{\hat{\alpha}_j^{\gamma}\right\}$ $(j = 1, \ldots, n)$ *are optimal solutions of the following models* 9A, 9B, 9C *respectively.*

$$\begin{aligned} &\min \frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}x_{ij}}{\sum_{j=1}^{n}x_{ij}} + \frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}z_{rj}}{\sum_{j=1}^{n}z_{rj}} \\ &s.t.\ \gamma \in E,\ C = \overline{C} \end{aligned} \tag{9A}$$

$$\begin{aligned} &\min \frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}x_{ij}}{\sum_{j=1}^{n}x_{ij}} + \frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}z_{rj}}{\sum_{j=1}^{n}z_{rj}} \\ &s.t.\ \gamma \in E,\ C = \widetilde{C} \end{aligned} \tag{9B}$$

$$\begin{aligned} &\min \frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}x_{ij}}{\sum_{j=1}^{n}x_{ij}} + \frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}z_{rj}}{\sum_{j=1}^{n}z_{rj}} \\ &s.t.\ \gamma \in E,\ C = \overline{C} + \widetilde{C} \end{aligned} \tag{9C}$$

Let $\alpha_j^{\gamma^{\#}} = \bar{\alpha}_j^{\gamma} + \tilde{\alpha}_j^{\gamma}$,
where $\gamma^{\#}$ *belongs to* $E = \left\{\gamma \middle| \sum_{j=1}^{n}\alpha_j^{\gamma}y_j \geqslant C = \overline{C} + \widetilde{C}, 0 \leqslant \alpha_j^{\gamma} \leqslant n_j, \alpha_j^{\gamma} \in N\right\}$.
Then $\left\{\alpha_j^{\gamma^{\#}} = \bar{\alpha}_j^{\gamma} + \tilde{\alpha}_j^{\gamma}\right\}$ $(j = 1, \ldots, n)$ *is a feasible solution of model* (9C).

Proof of Theorem 3. We have

$$\begin{aligned} &\frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\bar{\alpha}_j^{\gamma}x_{ij}}{\sum_{j=1}^{n}x_{ij}} + \frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\bar{\alpha}_j^{\gamma}z_{rj}}{\sum_{j=1}^{n}z_{rj}} + \frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\tilde{\alpha}_j^{\gamma}x_{ij}}{\sum_{j=1}^{n}x_{ij}} + \frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\tilde{\alpha}_j^{\gamma}z_{rj}}{\sum_{j=1}^{n}z_{rj}} = \frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma^{\#}}x_{ij}}{\sum_{j=1}^{n}x_{ij}} + \frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma^{\#}}z_{rj}}{\sum_{j=1}^{n}z_{rj}} \\ &\geqslant \min \frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}x_{ij}}{\sum_{j=1}^{n}x_{ij}} + \frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\alpha_j^{\gamma}z_{rj}}{\sum_{j=1}^{n}z_{rj}} = \frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\hat{\alpha}_j^{\gamma}x_{ij}}{\sum_{j=1}^{n}x_{ij}} + \frac{1}{r}\sum_{r=1}^{s}\frac{\sum_{j=1}^{n}\hat{\alpha}_j^{\gamma}z_{rj}}{\sum_{j=1}^{n}z_{rj}} \end{aligned}$$

This completes the proof. □

Theorem 3 implies that any decomposition of joint transportation will not perform better than the joint transportation, from the viewpoint of sustainability. Based on this, we have following suggestions for suppliers, manufacturers, retailers, and governments.

For suppliers, manufacturers, and retailers

Such companies should seek cooperators to do joint transport in SSCM. In fact, as clarified in the beginning of Section 'Disc ussion and recommendations', the inequality in $\sum_{j=1}^{n}\alpha_j^{\gamma}y_j \geqslant C$ may be strict when running the derived Pareto Optimal

Table 1
Data of 11 logistics companies.

Logistics company number	1	2	3	4	5	6	7	8	9	10	11
Number of transportation tools	68	89	81	56	24	26	50	32	28	26	21
Capacity per transportation tool	22	20	6	19	12	11	10	19	16	21	6
Capital cost per transportation tool	3.11	2.68	1.66	2.36	5.71	3.69	3.13	2.27	3.24	3.52	7.04
Labor per transportation tool	8	6	6	6	9	7	4	8	5	6	9
Energy consumption per transportation	5.17	6.17	2.73	5.47	9.66	5.99	2.11	9.90	12.14	11.09	1.52
CO_2 emission per transportation tool	4.77	2.41	5.41	3.06	6.90	6.70	2.45	5.39	4.37	3.22	6.07

Table 2a
Derived transportation strategy for manufacturer.

Logistics company number		1	2	3	4	5	6	7	8	9	10	11
Number of transportation tools		68	89	81	56	24	26	50	32	28	26	21
Transportation strategy for manufacturer	$C = 3000$	–	89	–	56	–	–	1	–	–	7	–
	$C = 4000$	33	89	–	56	–	–	1	–	–	20	–

Table 2b
Total resources consumption and pollutant emission of the derived transportation strategy.

	Total capacity	Total capital cost	Total labor	Total energy consumption	Total CO_2 emission
$C = 3000$	3001	398.77	941	938.42	414.70
$C = 4000$	4000	547.10	1297	1253.04	613.93

transportation strategy. This implies that the waste of transportation capacity may exist when a single company hires logistics companies to transport its product. This waste of transportation capacity will lead to a waste of capital, since the logistics companies will not offer any discounts for the unused capacity. Since Theorem 3 has proved that the joint transportation will not perform worse than its any decomposition, the companies should seek suitable cooperators to do joint transport. The empirical study contained in Section 'Empirical study' further shows the existence of such cooperators.

For governments

Governments should promote centralized transportation for SSCM. The resources of transportation, like transportation tools and capacities, are limited in the market. If all stakeholders are totally freely competing for transportation resources, the benefit of the whole industry will be damaged even the Joint Transportation Policy is well done. So in the non-profit industries, governments should promote centralized transportation, and do find industry-level Pareto Optimal transportation strategies.

Empirical study

We apply our approach to an empirical study of design sustainable transportation mechanism for one Chinese air-condition manufacturer to transport its products. In the scenario, there are 11 logistics companies for the manufacturer to choose from. To get the Pareto Optimal transportation strategy, we take 2 economic indices (capital cost, energy consumption), 1 social index (labor) and 1 environmental index (CO_2 emission) into consideration. All data of 11 logistics companies are listed in Table 1 above.

The derived Pareto Optimal transportation strategy, together with its corresponding total resources consumption and pollutant emission, is contained in Tables 2a and 2b. According to Table 2a, when the amount of products that need to be transported is 3000, i.e. $C = 3000$, the derived Pareto Optimal transportation strategy for the manufacturer should be to hire 89, 56, 1 and 7 tools from the 2nd, 4th, 7th and 10th logistics company respectively. When C turns to be 4000, the manufacturer should extra hire 33 tools from the 1st logistics company and 13 tools from the 10th logistics company.

In addition, there has an interesting research finding in Table 2b that need to be pointed out. When $C = 3000$, the total capacity of the derived transportation strategy is 3001. When $C = 4000$, the total capacity of the derived transportation strategy is 4000. This implies that when the manufacturer is planning to transport 3000 products, it could make full use of the capacity and realize sustainability simultaneously via cooperating with the one that need to transport 1000 products. This research finding have further demonstrated the value of the Joint Transportation Policy proposed in Section 'Discussion and recommendations'.

Actually, we have theoretically proved that the transportation strategy derived from model (4) is Pareto Optimal. Next, we give a comparison between the derived Pareto Optimal transportation strategy and several other feasible transportation

Table 3
Comparison between derived Pareto Optimal transportation strategy and other feasible transportation schemes.

	Total capacity	Total capital cost		Total labor		Total energy consumption		Total CO_2 emission	
Derived transportation strategy ($C = 3000$)	3001	398.77		941		938.42		414.7	
Replace 1 unit LC_7 with other feasible options	3013	398.75	–	945	+	938.46	+	413.34	–
	3003	398.96	+	949	+	938.74	+	419.38	+
	3003	401.35	+	946	+	942.95	+	415.47	+
	3002	399.33	+	944	+	939.28	+	415.27	+
	3010	397.91	–	945	+	943.19	+	413.96	–
	3007	398.88	+	942	+	945.43	+	412.94	–
	3012	399.16	+	943	+	944.38	+	411.79	–
	3003	409.71	+	955	+	936.34	–	420.71	+
Replace 1 unit LC_{10} with other feasible options	3002	398.36	–	943	+	932.50	–	416.25	+
	3004	401.89	+	958	+	938.23	+	433.11	+
	3004	406.67	+	953	+	946.64	+	425.28	+
	3002	402.63	+	949	+	939.30	+	424.89	+
	3000	401.51	+	943	+	931.55	–	416.38	+
	3018	399.79	+	952	+	947.13	+	422.25	+
	3012	401.72	+	945	+	951.61	+	420.22	+
	3004	423.39	+	972	+	933.42	–	435.76	+
Replace 1 unit LC_4 with other feasible options	3004	399.52	+	943	+	938.12	–	416.41	+
	3000	401.39	+	952	+	941.13	+	427.86	+
	3006	407.83	+	953	+	952.26	+	425.44	+
	3004	403.79	+	949	+	944.92	+	425.05	+
	3002	402.67	+	943	+	937.17	–	416.54	+
	3001	398.68	–	943	+	942.85	+	417.03	+
	3014	402.88	+	945	+	957.23	+	420.38	+
	3003	399.93	+	941	+	944.04	+	414.86	+
	3000	417.52	+	963	+	937.52	–	429.85	+
Replace 1 unit LC_2 with other feasible options	3003	399.20	+	943	+	937.42	–	417.06	+
	3005	402.73	+	958	+	943.15	+	433.92	+
	3005	407.51	+	953	+	951.56	+	426.09	+
	3003	403.47	+	949	+	944.22	+	425.70	+
	3001	402.35	+	943	+	936.47	–	417.19	+
	3000	398.36	–	943	+	942.15	+	417.68	+
	3013	402.56	+	945	+	956.53	+	421.03	+
	3002	399.61	+	941	+	943.34	+	415.51	+
	3005	424.23	+	972	+	938.34	–	436.57	+

schemes via replacing 1 unit chosen transportation tool in the derived strategy with suitable other options. The results of the comparison are contained in Table 3 below.

According to Table 3, it can be found that there has no one feasible transportation scheme that Pareto dominates the derived strategy. Actually, there only 14.7% feasible transportation schemes have less capital cost than the derived strategy, about 29.4% have less energy consumption and only 11.8% has less CO_2 emission. Further, there no one feasible transportation scheme has less labor cost than the derived strategy. We can find that the derived strategy has Pareto dominated more than 52.9% feasible schemes.

Conclusion and extension

This paper has addressed the issue of eco-design for transportation in sustainable supply chain management. A novel model is provided for suppliers, manufacturers, and retailers to seek suitable sustainable transportation schemes, and a tractable algorithm to solve the model has been proposed. The main theoretical and practical contributions of this work are reflected in the following aspects.

Firstly, the proposed model is developed based upon the theory of data envelopment analysis, thus the derived eco-design for transportation in SSCM is provably Pareto Optimal, meaning that it can fully meet the core demand of sustainability. By applying the derived transportation strategy in practice, the stakeholders can achieve their goals of transportation with less resource consumption and pollution emission, thereby improving the corresponding performance in SSCM.

Secondly, the alternative algorithm developed in Section 'Solution method' will have an obvious advantage in finding a Pareto Optimal solution of the proposed model when huge data sets are in play. Thus the results of this research show good tractability and can be used easily in the real world.

Lastly, a heuristic joint transportation policy has resulted from the discussion in Section 'Discussion and recommendations'. This heuristic policy implies that firms can gather together to have joint transportation and earn extra benefits in both economic and environmental areas. Theorem 3 has theoretically proved that joint transportation and joint replenishment do have advantages in environmental management as well as their well-known advantages in operations management. Thus this research can be seen as a significant supplement to the theory of operations management as well.

This work can be extended in at least two directions. First, undesirable outputs are treated as inputs in this paper. There are several other possible treatments in conventional DEA theory, and the proposed model could be extended with these treatments via suitable adjustments. Second, the scenario in this research is deterministic, whereas in real world conditions there might be some random variables. Extending the proposed model to be a stochastic one might be difficult, but it is worthy of research.

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