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Sustainability assessment of supply chains by inverse network dynamic data envelopment analysis

M. Kalantary^a, R. Farzipoor Saen^b, and A. Toloie Eshlaghy^{a,*}

a. *Department of Industrial Management, Science and Research Branch, Islamic Azad University, Tehran, Iran.*

b. *Department of Industrial Management, Karaj Branch, Islamic Azad University, Karaj, Iran.*

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 Dynamic DEA.

Abstract. This paper focuses on assessing sustainability of supply chains. This paper, at first, proposes network dynamic Range Adjusted Measure (RAM) model. Then, an inverse version of network dynamic RAM model is proposed. The proposed inverse network dynamic Data Envelopment Analysis (DEA) model changes both inputs and outputs of Decision-Making Units (DMUs) so that existing efficiency scores of DMUs remain unchanged. We change inputs and outputs without any modification in efficiency score of DMU under evaluation, while inputs and outputs may have a large range. A case study shows the efficacy of the proposed model.

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1. Introduction

Nowadays, our earth encounters a number of difficulties such as air pollution, little or lack of water resources, energy inefficiency, destruction of forests, etc. For this reason, supply chains should be responsible for environmental issues. Mentzer et al. [1] defined Supply Chain Management (SCM) as “the systemic, strategic coordination of traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole”. Drumwright [2] and Murphy et al. [3] introduced Sustainable Supply Chain

Management (SSCM). Carter and Rogers [4] defined SSCM as “the strategic, transparent integration and achievement of an organization’s social, environmental, and economic goals in the systemic coordination of key inter-organizational business processes for improving the long-term economic performance of the individual company and its supply chains”. At the moment, sustainability considerations are not just a symbolic action; however, they are reactive to pressures of Non-Governmental Organizations (NGOs), media, and green political parties [5]. Many firms have established tough evaluations for suppliers in their supply chain to ensure that the sustainability considerations are addressed seriously [6–8].

Charnes et al. [9] proposed Data Envelopment Analysis (DEA). DEA is a proper tool for assessing relative efficiency of supply chains [10]. In classical DEA models, Decision-Making Units (DMUs) are considered as a black box. Lewis and Sexton [11] proposed a network DEA model to deal with divisions in each DMU. In addition, most of other traditional DEA models measure efficiency score just in a specific

*. *Corresponding author.*

E-mail addresses: majidkalantary.pm@gmail.com (M. Kalantary); farzipour@yahoo.com (R. Farzipoor Saen); toloie@gmail.com (A. Toloie Eshlaghy).

period. For the first time, Färe and Grosskopf [12] proposed dynamic DEA model. Tone and Tsutsui [13] considered the network DEA model dynamically and, then, proposed a network dynamic DEA model based on Slacks-Based Measure (SBM) approach. They named efficiencies of each period and each division as “term” and “divisional” efficiencies, respectively.

This paper proposes input-oriented Range Adjusted Measure (RAM) model and clarifies the reason for using this model. Then, an inverse model of network dynamic input/output-oriented RAM is proposed. To the best of our knowledge, the inverse RAM model with network and dynamic structure has not been proposed so far. This paper has the following contributions: the following topics are proposed in this paper for the first time:

- Input/output-oriented RAM model with dynamic and network structure is developed;
- The inverse model of dynamic-network input/output-oriented RAM model is developed;
- Both inputs and outputs of Decision-Making Units (DMUs) can be changed in our inverse DEA model;
- The proposed model is applied to the assessment of the sustainability of supply chains;
- To demonstrate the applicability of our model, a case study is given.

The main objective of this paper is to develop network-dynamic input-oriented RAM model and its inverse for assessing sustainability of supply chains.

The structure of this paper is organized as follows. Literature review is presented in Section 2. The proposed models are given in Section 3. A case study is given in Section 4. Managerial implications and conclusions are explained in Sections 5 and 6, respectively.

2. Literature review

2.1. Sustainable SCM

As mentioned earlier, environmental and social responsibilities in SCM started to receive attention in 1994 and continued through researches such as greening supply chain [14], greening product [15,16], and greening supply chain from product design to end user [17,18].

Liu et al. [19] focused on eco-friendly competition between substitutable products and retail stores. They found that eco-friendly manufacturers earned more profits because of customers' environmental awareness. Zhang et al. [20] studied impact of customers' environmental awareness on companies. Ghosh and Shah [21] discussed greening costs and impact of greening sensitivity of customers on profit. Xie [22] studied the role of policy-makers in energy saving.

Assessing sustainability of supply chains is an important topic. Genovese et al. [23] proposed an environmentally extended Multi-Regional Input-Output (MRIO) hybrid model and Life Cycle Assessment (LCA) that can be used for emissions assessment of supply chains. They evaluated supply chains based on emissions. Su et al. [24] addressed improving sustainability of supply chain management in situations with incomplete information. They proposed a hierarchical grey-DEMATEL approach. Dubey et al. [25] focused on dynamic nature of SSCM. They addressed both quantitative and qualitative approaches. Kumar et al. [26] assessed suppliers based on SSCM criteria. They applied fuzzy multi-criteria decision-making model. Azadi et al. [27] developed a fuzzy model for assessing sustainability of suppliers in terms of economic, environmental, and social factors. Li and Cui [28] proposed network range adjusted measure model to evaluate sustainability of supply chains. Table 1 summarizes previous researches on sustainable SCM criteria and used techniques.

This paper proposes inverse network dynamic input-oriented RAM model to assess sustainability of supply chains as well as given economic, environmental, and social criteria.

2.2. Data Envelopment Analysis (DEA)

2.2.1. Inverse DEA

Wei et al. [37], for the first time, proposed inverse DEA model. The main purpose of the inverse DEA model is to analyze sensitivity of a DEA model to changes in inputs/outputs of DMU_o (DMU under evaluation) without any change in DMU_o efficiency score. In other words, after changes in inputs/outputs, Production Possibility Set (PPS) changes; however, efficient frontier should not be changed dramatically [38].

Yan et al. [38] introduced an inverse DEA model for resource planning, given decision-makers' preferences. Jahanshahloo et al. [39] developed the inverse model of Yan et al. [38] and presented inverse DEA model to estimate outputs, given changes in inputs. Jahanshahloo et al. [40] developed an inverse DEA model to estimate inputs, given outputs increase and improvements in efficiency score. Furthermore, they estimated maximum reduction in inputs without changing efficiency scores. Jahanshahloo et al. [41] ran a sensitivity analysis by inverse DEA model. They determined upper and lower bounds for inputs and outputs by two multi-objective linear programming problems and converted multi-objective linear programme to a linear program. Jahanshahloo et al. [42] addressed inter-temporal dependency among efficiencies of a DMU_o in multiple periods. They proposed inverse dynamic DEA model. Furthermore, they introduced a periodic weak Pareto solution in multiple-objective linear programming. Lertworasirikul et al. [43] proposed inverse

Table 1. Sustainable SCM criteria and different approaches for assessing sustainability.

Authors	Approaches and techniques	Sustainable SCM criteria
Awasthi et al. [29]	Fuzzy Multi-Criteria Decision Making (MCDM)	Environmental criteria
Büyükoçkan et al. [30]	Fuzzy MCDM in the presence of incomplete information	Environmental and economic criteria
Erol et al. [31]	Fuzzy MCDM	Environmental criteria
Govindan et al. [32]	Fuzzy MCDM based on triple bottom line approach	Environmental and economic criteria
Kuo et al. [33]	Artificial neural network and MADM	Environmental, social, and economic criteria
Punniyamoorthy et al. [34]	Structural equation modeling in fuzzy context	Economic criteria
Amindoust et al. [35]	Fuzzy inference system ranking model	Environmental, social, and economic criteria
Yeh and Chuang [36]	MCDM by use of Genetic Algorithm	Environmental and economic criteria
Azadi et al. [27]	Enhanced Russell measure DEA model in fuzzy context	Environmental, social, and economic criteria

DEA model based on linear programming and Pareto optimal solution. Their main DEA model is based upon BCC (Banker-Charnes-Cooper) model [44].

Amin et al. [45] merged a couple of DMUs and studied whether or not the merged DMU could affect efficiency frontier. Amin et al. [46] used inverse DEA model to recommend higher operational efficiency. Eyni et al. [47] divided inputs/outputs into desirable and undesirable inputs/outputs and applied inverse DEA model to increase desirable outputs and decrease undesirable outputs.

2.2.2. RAM model

In real world, there are differences in measurement unit of variables. In addition, in some cases, there might be big ranges in inputs and outputs. Some DEA models can cope with different measurement units, which are called unit invariant models [48]. For instance, CCR [9] and BCC [44] models are considered as unit invariant models. On the other hand, there might be zero and negative values in datasets [49]. Some of DEA models can deal with negative and zero values called translation invariant, i.e., translation of values does not affect results [50]. Additive (ADD) model and BCC model are translation invariant, although the input-oriented

BCC is invariant under output translation, and vice versa [51]. RAM is an extension of the ADD model, which is both unit and translation invariant [52].

In this paper, a new extension of RAM model is introduced, which is called input/output oriented-RAM model (oriented-RAM). Moreover, the inverse oriented-RAM model with network and dynamic structure is proposed.

2.2.3. Network and dynamic DEA models

Tone and Tsutsui [53] argued that traditional DEA models dealt with DMUs as black boxes and could not address network structure of DMUs. They proposed a network SBM model and calculated “divisional efficiency” of each division in each DMU. Färe and Grosskopf [54], for the first time, addressed intermediate products and, then, extended their work and developed network DEA model [55]. Sexton and Lewis [56] proposed a two-stage DEA model and extended their work to multi-stage networks. Mirhedayatian et al. [57] proposed a network DEA model to assess green supply chains.

Färe and Grosskopf [12] first introduced dynamic DEA. Tone and Tsutsui [58] proposed a dynamic SBM measure and calculated “term efficiency” for each DMU

in each period. Chen [59] proposed a network DEA model with dynamic effects on network. Park and Park [60] expanded Debreu-Farrell technical efficiency and applied their multi-period model to cable TV service units. Shabanpour et al. [61] utilized dynamic DEA and artificial neural networks to evaluate past, present, and future efficiencies of green supply chains. Tone and Tsutsui [13] combined network and dynamic DEA models and proposed network dynamic DEA model.

3. The proposed models

3.1. Oriented-RAM model

Basic RAM model proposed by Cooper et al. [52] is as follows:

$$\begin{aligned} \max \quad & \theta = \frac{1}{m+p} \left(\sum_{i=1}^m R_i^x s_i^x + \sum_{r=1}^p R_r^y s_r^y \right), \\ \text{s.t.:} \quad & \\ & \sum_j^n x_{ij} \lambda_j + s_i^x = x_{io}, \quad i = 1, \dots, m, \\ & \sum_j^n y_{rj} \lambda_j - s_r^y = y_{ro}, \quad r = 1, \dots, p, \\ & \lambda_j, s_i^x, s_r^y \geq 0, \quad \forall i, j, r, \end{aligned} \quad (1)$$

where s_i^x and s_r^y are distances of DMU_o from efficient frontier. R_i^x and R_r^y denote ranges of inputs and outputs calculated as $1/(x_i^U - x_i^L)$ and $1/(y_r^U - y_r^L)$, respectively. Upper and lower bounds are specified by $x_i^U = \max_j \{x_{ij}\}$, $y_r^U = \max_j \{y_{rj}\}$ as well as $x_i^L = \min_j \{x_{ij}\}$, $y_r^L = \min_j \{y_{rj}\}$, respectively. Objective function measures inefficiency of DMU_o. Efficiency score is calculated by $\theta^* = 1 - (1/m+p)(\sum_{i=1}^m R_i^x s_i^{x*} + \sum_{r=1}^p R_r^y s_r^{y*})$. A DMU_o (supply chain) is efficient if the objective function of Model (1) is zero, i.e., $s_i^{x*} = s_r^{y*} = 0$. Our new input-oriented RAM model is as follows:

$$\begin{aligned} \max \quad & \frac{1}{m} \sum_{i=1}^m R_i^x s_i^x, \\ \text{s.t.:} \quad & \\ & \sum_j^n x_{ij} \lambda_j + s_i^x = x_{io}, \quad i = 1, \dots, m, \\ & \sum_j^n y_{rj} \lambda_j \geq y_{ro}, \quad r = 1, \dots, p, \\ & \sum_j^n \lambda_j = 1, \end{aligned}$$

$$\lambda_j, s_i^x \geq 0, \quad \forall i, j, r, \quad (2)$$

where R_i^x is $1/(x_i^U - x_i^L)$.

The reason for proposing the oriented-RAM model is that, in real world, some cases exist in which there might be very a high range of inputs or outputs. On the other hand, in some cases, such as production plants, divisions produce intermediate measures delivered to next divisions. Thus, except for the last division, other divisions cannot deliver outputs to outside of the network (e.g., water refinery). Therefore, ordinary RAM model cannot be utilized. There is a significant difference between our model and the other unit and translation invariant DEA models. Our idea originates from input (output) oriented SBM model proposed by Cooper et al. [51].

Theorem 1. In optimal solution, efficiency score is $0 \leq \theta^* \leq 1$.

Proof. According to Aida et al. [62], in an optimal solution, there is:

$$0 \leq - \sum_j^n x_{ij} \lambda_j^* + x_{io} = s_i^{x*} \leq x_i^U - x_i^L. \quad (3)$$

Eq. (3) comes from condition $\sum_j^n \lambda_j = 1$. Therefore, we have:

$$0 \leq R_i^x s_i^{x*} \leq 1. \quad (4)$$

■

Theorem 2. The RAM model is translation invariant. This theorem can be generalized for input-oriented RAM model. Suppose that there are n DMUs with one input and one output. Changes after translation are depicted in Figures 1, 2, and 3.

As is observed, in Figures 1, 2, and 3, translation cannot change direction or amount of efficiency improvement.

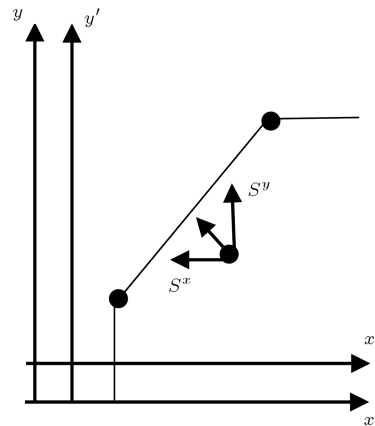


Figure 1. Basic RAM.

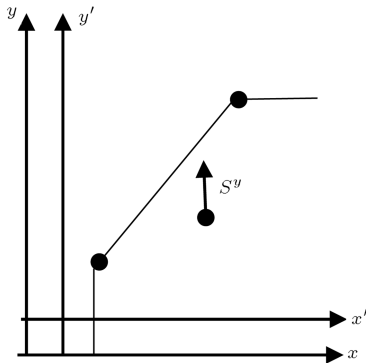


Figure 2. Output oriented-RAM model.

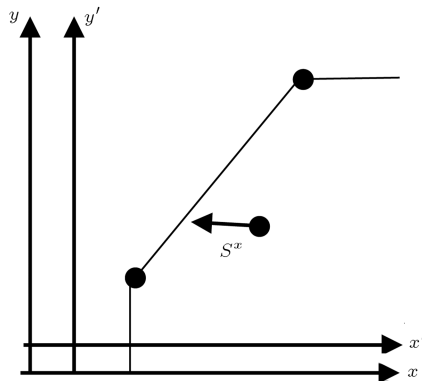


Figure 3. Input oriented-RAM model.

Proof. For proof, see Cooper et al. [63]. ■

Theorem 3. The input-oriented RAM model is unit invariant in inputs. In addition, output-oriented RAM model is unit invariant in outputs, corresponding to the objective function of input (output)-oriented RAM model (Model 2). As is seen, there are only inputs' (outputs') slacks in the objective function.

Now, output-oriented RAM model is proposed. Model (5) has characteristics similar to those of Model (2):

$$\begin{aligned}
 \max \quad & \frac{1}{p} \sum_{r=1}^p R_r^y s_r^y, \\
 \text{s.t.} \quad & \\
 & \sum_j^n x_{ij} \lambda_j \leq x_{io}, \quad i = 1, \dots, m, \\
 & \sum_j^n y_{rj} \lambda_j - s_r^y = y_{ro}, \quad r = 1, \dots, p, \\
 & \sum_j^n \lambda_j = 1, \\
 & \lambda_j, s_r^y \geq 0, \quad \forall i, j, r.
 \end{aligned} \tag{5}$$

Proof. For proof, see Cooper et al. [63]. ■

3.2. Network-dynamic input-oriented RAM (NDIO-RAM) model

In this subsection, we extend the input-oriented RAM model to a network dynamic model. Suppose that there are n DMUs ($j = 1, \dots, n$) with k divisions ($k = 1, \dots, K$) in each t period ($t = 1, \dots, T$). Notations are as follows:

x_{ijk}^t	The i th input of the j th DMU in the k th division in term t ;
y_{rjk}^t	The r th output of the j th DMU in the k th division in term t ;
$l_{wj(k-h)}^t$	The w th ($w = 1, \dots, W$) intermediate measure of the j th DMU sent from the k th division to the h th division in term t ;
$c_{ujk}^{t,t+1}$	The u th ($u = 1, \dots, U$) carry-over of the j th DMU in the k th division from term t to term $t + 1$;
λ_{jk}^t	Intensity vector of the j th DMU in the k th division in term t .

At this juncture, the NDIO-RAM model is proposed as follows:

$$\begin{aligned}
 \max \quad & \frac{1}{T} \sum_{t=1}^T \frac{1}{K} \sum_{k=1}^K \frac{1}{m} \sum_{i=1}^m R_{io k}^{x^t} s_{io k}^{x^t}, \\
 \text{s.t.} \quad & \\
 & \sum_j^n x_{ijk}^t \lambda_{jk}^t + s_{io k}^{x^t} = x_{io k}^{x^t}, \\
 & i = 1, \dots, m, \quad \forall K, T, \\
 & \sum_j^n y_{rjk}^t \lambda_{jk}^t \geq y_{ro k}^t, \quad r = 1, \dots, p, \quad \forall K, T, \\
 & \sum_j^n l_{wj(k-h)}^t \lambda_{jk}^t = \sum_j^n l_{wj(k-h)}^t \lambda_{jh}^t, \\
 & w = 1, \dots, W, \quad \forall K, T, \\
 & \sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t = \sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^{t+1}, \\
 & u = 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K, \\
 & \sum_j^n \lambda_{jk}^t = 1, \quad \forall K, T,
 \end{aligned}$$

$$\lambda_{jk}^t, s_{io k}^{x^t} \geq 0, \quad \forall i, j, r. \quad (6)$$

Model (6) is a general model in which there is no preference for divisions, inputs, and terms. Intermediate measures and carry-overs have indirect impact on objective function.

3.3. Inverse oriented-RAM model

For the first time, Wei et al. [37] introduced the following inverse (Models (7) and (8)). Their inverse model was derived from a general radial output-oriented DEA model.

$$\begin{aligned} \max \quad & z_0, \\ \text{s.t.:} \quad & \\ & \sum_j^n x_{ij} \lambda_j \leq x_{io}, \quad i = 1, \dots, m, \\ & \sum_j^n y_{rj} \lambda_j \geq y_{ro} z_0, \quad r = 1, \dots, p, \\ & \delta_1 \left(\sum_j^N \lambda_j + \delta_2 (-1)^{\delta_3} v \right) = \delta_1, \\ & \lambda_j, v \geq 0, \quad \forall i, j, r. \end{aligned} \quad (7)$$

Parameters δ_1 , δ_2 , and δ_3 can have only 0 or 1 values:

- If $\delta_1 = 0$, then Model (7) is a CCR model;
- If $\delta_1 = 1$ and $\delta_2 = 0$, then Model (7) is a BCC model;
- If $\delta_1 = \delta_2 = 1$ and $\delta_3 = 0$, then Model (7) is a non-increasing model;
- If $\delta_1 = \delta_2 = \delta_3 = 1$, then Model (7) is a non-decreasing model.

Wei et al. [37] supposed that inputs of DMU_o (x_{io}) increased to a given value, i.e., a_i . Then, they tried to determine proper values for β_r given that objective function values of Models (7) and (8) are equal, i.e., $z_o^* = z_{inv}^*$. Wei et al. [37] proposed a new dummy DMU_{n+1} with input vector a_{io} and output vector β_{ro} , where $a_{io} = x_{io} + \Delta x_{io}$ and $\beta_{ro} = y_{ro} + \Delta y_{ro}$.

$$\begin{aligned} \max \quad & z_{inv}, \\ \text{s.t.:} \quad & \\ & \sum_j^n x_{ij} \lambda_j + \alpha_{io} \lambda_{n+1} \leq \alpha_{io}, \quad i = 1, \dots, m, \\ & \sum_j^n y_{rj} \lambda_j + \beta_{ro} \lambda_{n+1} \geq \beta_{ro} z_{inv}, \quad r = 1, \dots, p, \end{aligned}$$

$$\begin{aligned} \delta_1 \left(\sum_j^N \lambda_j + \lambda_{n+1} + \delta_2 (-1)^{\delta_3} v \right) &= \delta_1, \\ \lambda_j, v &\geq 0, \quad \forall i, j = 1, 2, \dots, n+1, r. \end{aligned} \quad (8)$$

In our proposed model, there are not any given predetermined values for neither a_{io} nor β_{ro} . Model (13) is a multi-objective linear programme that determines a_{io} and β_{ro} .

Definition 1. Let the optimal solution for the following input-oriented RAM model be $(z_0^*, \lambda_j^*, s_i^{x*})$:

$$\begin{aligned} \max \quad & z_0 = \frac{1}{m} \sum_{i=1}^m R_i^x s_i^x, \\ \text{s.t.:} \quad & \\ & \sum_j^n x_{ij} \lambda_j + s_i^x = x_{io}, \quad i = 1, \dots, m, \\ & \sum_j^n y_{rj} \lambda_j \geq y_{ro}, \quad r = 1, \dots, p, \\ & \sum_j^n \lambda_j = 1, \\ & \lambda_j, s_i^x \geq 0, \quad \forall i, j, r. \end{aligned} \quad (9)$$

Definition 2. The input-oriented RAM inverse model can be formulated as Model (10), and its optimal solution is $(z_{inv}^*, \lambda_j^*, \lambda_{j+1}^*, s_i^{\bar{\alpha}*})$:

$$\begin{aligned} \max \quad & z_{inv} = \frac{1}{m} \sum_{i=1}^m R_i^x s_i^{\bar{\alpha}}, \\ \text{s.t.:} \quad & \\ & \sum_j^n x_{ij} \lambda_j + \bar{\alpha}_{io} \lambda_{n+1} + s_i^{\bar{\alpha}} = \bar{\alpha}_{io}, \\ & i = 1, \dots, m, \\ & \sum_j^n y_{rj} \lambda_j + (y_{ro} + \Delta \bar{y}_{ro}) \lambda_{n+1} \geq y_{ro} + \Delta \bar{y}_{ro}, \\ & r = 1, \dots, p, \\ & \sum_j^n \lambda_j + \lambda_{n+1} = 1, \\ & \lambda_j, \lambda_{n+1}, s_i^{\bar{\alpha}} \geq 0, \quad \forall i, j, r. \end{aligned} \quad (10)$$

Given the assumption, z_0^* from Model (9) and z_{inv}^* from Model (10) have similar values. In addition,

R_i^x is assumed constant as we want to keep efficiency frontier unchanged. Therefore, the following equation is considered:

$$\frac{1}{m} \sum_{i=1}^m R_i^x s_i^{x*} = \frac{1}{m} \sum_{i=1}^m R_i^x s_i^{\bar{\alpha}*}. \quad (11)$$

As a result:

$$s_i^{x*} = s_i^{\bar{\alpha}*}. \quad (12)$$

Now, a multi-objective linear programme (13) is utilized that determines α_{io} and Δy_{ro} , simultaneously, where $\alpha_{io} = x_{io} + \Delta x_{io}$:

$$\begin{aligned} \min \quad & \alpha_{io}, \\ \text{s.t.:} \quad & \\ & \sum_j^n x_{ij} \lambda_j + s_i^{x*} = \alpha_{io}, \quad i = 1, \dots, m, \\ & \sum_j^n y_{rj} \lambda_j = y_{ro} + \Delta y_{ro}, \quad r = 1, \dots, p, \\ & \alpha_{io} \geq x_{io}, \\ & \lambda_j \geq 0, \quad \forall i, j, r, \\ & \Delta y_{ro} : \text{free}. \end{aligned} \quad (13)$$

In the first constraint of Model (13), s_i^α is replaced by s_i^{x*} . R_i^x is assumed to be constant. The last condition of Model (13) guarantees that purpose.

Definition 3. Suppose that $\bar{\alpha}_{io}$, $\Delta \bar{y}_{ro}$, and $\bar{\lambda}_j$ are feasible solutions. If there is no feasible solution such as $\alpha_i < \bar{\alpha}_{io}$, $(\bar{\alpha}_{io}, \Delta \bar{y}_{ro}, \bar{\lambda}_j)$ can be a weak Pareto solution for Model (13).

Theorem 4. $(\bar{\alpha}_{io}, \Delta \bar{y}_{ro}, \bar{\lambda}_j)$ is a weak Pareto solution for Model (13) and z_o^* is the optimal objective function value for Model (9). z_{RA}^* is the optimal objective function value for Model (14):

$$\begin{aligned} \max \quad & z_{RA} = \frac{1}{m} \sum_{i=1}^m R_i^x s_i^\alpha, \\ \text{s.t.:} \quad & \\ & \sum_j^n x_{ij} \lambda_j + s_i^\alpha = \bar{\alpha}_{io}, \quad i = 1, \dots, m, \\ & \sum_j^n y_{rj} \lambda_j \geq y_{ro} + \Delta \bar{y}_{ro}, \quad r = 1, \dots, p, \\ & \sum_j^n \lambda_j = 1, \end{aligned}$$

$$\lambda_j, s_i^\alpha \geq 0, \quad \forall i, j, r. \quad (14)$$

Proof. Model (14) has an optimal solution $(z_{RA}^*, \lambda_j^\alpha, s_i^{\alpha*})$. The optimal solution of Model (13) is embedded in its first constraint and that of Model (14) in its first constraints. Therefore, given Model (13), we have:

$$\sum_j^n x_{ij} \bar{\lambda}_j + s_i^{x*} = \bar{\alpha}_{io}. \quad (15)$$

In addition, given Model (14), we have:

$$\sum_j^n x_{ij} \lambda_j^\alpha + s_i^{\alpha*} = \bar{\alpha}_{io}. \quad (16)$$

Consequently:

$$\sum_j^n x_{ij} \lambda_j^\alpha + s_i^{\alpha*} = \sum_j^n x_{ij} \bar{\lambda}_j + s_i^{x*}. \quad (17)$$

Furthermore, given Definition 3 and Model (14), we know the optimal solution of Model (13), and $(\bar{\alpha}_{io}, \Delta \bar{y}_{ro}, \bar{\lambda}_j)$ is a feasible solution for Model (14). Given Models (9) and (14) and Definition 3, we have:

$$z_{RA}^* \geq z_o^*. \quad (18)$$

As mentioned earlier, R_i^x remains constant. Therefore:

$$s_i^{\alpha*} \geq s_i^{x*}. \quad (19)$$

If $z_{RA}^* > z_o^*$, then:

$$s_i^{\alpha*} > s_i^{x*}. \quad (20)$$

By Eqs. (17) and (20), we have:

$$\sum_j^n x_{ij} \lambda_j^\alpha < \sum_j^n x_{ij} \bar{\lambda}_j. \quad (21)$$

To convert Expression (21) to an equation, $h > 0$ is added to left-hand side of Expression (21).

$$\sum_j^n x_{ij} \lambda_j^\alpha + h = \sum_j^n x_{ij} \bar{\lambda}_j. \quad (22)$$

Now, we substitute $\sum_j^n x_{ij} \lambda_j^\alpha + h$ by $\sum_j^n x_{ij} \bar{\lambda}_j$ in the first constrain of Model (13).

$$\sum_j^n x_{ij} \lambda_j^\alpha + s_i^{x*} = \bar{\alpha}_{io} - h. \quad (23)$$

Therefore, we have a feasible solution $(\lambda_j^\alpha, \bar{\alpha}_{io} - h)$ for Model (13), while we know that Model (13) has a weak Pareto solution $(\bar{\alpha}_{io}, \bar{\lambda}_j)$. Therefore, we have $z_{RA}^* = z_o^*$. Then, $h = 0$. By Theorem 4, the relationship between Models (14) and (13) is examined. ■

Theorem 5. Models (9) and (14) have similar objective function values: $z_{RA}^* = z_o^*$.

Proof. Given Theorem 4, we know that $s_i^{\alpha*} = s_i^{x*}$. Thus, there is $\frac{1}{m} \sum_{i=1}^m R_i^x s_i^{\alpha*} = \frac{1}{m} \sum_{i=1}^m R_i^x s_i^{x*}$. ■

Theorem 6. Models (10) and (14) have similar objective function values: $z_{RA}^* = z_{inv}^* s$.

Proof. Let $(z_{inv}^*, \lambda_j^*, \lambda_{j+1}^*, s_i^{\alpha*})$ be the optimal solution of Model (10) and $z_{inv}^* \geq 0$. We suppose that $z_{inv}^* > 0$. If $z_{inv}^* > 0$, then $\lambda_{n+1} = 0$. In this case, we add a new constraint ($\lambda_{n+1} = 0$) to Model (10) so that it becomes similar to Model (14). We can prove it by another manner. The dual of Model (10) is as follows:

$$\begin{aligned} \min \quad & \sum_i^m v_i \bar{\alpha}_{iO} - \sum_r^p u_r (\bar{y} + \Delta \bar{y}_{ro}) + \theta, \\ \text{s.t.:} \quad & \\ & \sum_i^m v_i x_{iO} - \sum_r^p u_r y_{rj} + \theta \geq 0, \quad \forall j, \\ & \sum_i^m v_i \bar{\alpha}_{iO} - \sum_r^p u_r (\bar{y} + \Delta \bar{y}_{ro}) + \theta \geq 0, \\ & v_i \geq \frac{1}{m R_i^x}, \quad \forall i, \\ & v_i, \theta : \text{free}, \quad u_r \geq 0, \quad j = 1, 2, \dots, n. \end{aligned} \quad (24)$$

Given the relationship between primal and dual problems [64], objective function value of Model (24) is similar to that of Model (10). Therefore, the second constraint of Model (24) should be an inequality. Thus, this constraint is redundant. Consequently, Model (24) is similar to Model (25). The only difference between Model (24) and Model (25) is the second constraint of Model (24).

$$\begin{aligned} \min \quad & \sum_i^m v_i \bar{\alpha}_{iO} - \sum_r^p u_r (\bar{y} + \Delta \bar{y}_{ro}) + \theta, \\ \text{s.t.:} \quad & \\ & \sum_i^m v_i x_{iO} - \sum_r^p u_r y_{rj} + \theta \geq 0, \quad \forall j, \\ & v_i \geq \frac{1}{m R_i^x}, \quad \forall i, \\ & v_i, \theta : \text{free}, \quad u_r \geq 0, \quad j = 1, 2, \dots, n. \end{aligned} \quad (25)$$

Note that Model (25) is the dual of Model (10). In Model (10), the first set of constraints has equity sign. Therefore, the related dual variable (v_i) is free in sign.

Theorem 7. Let $(z_o^*, \lambda_j^*, \text{ and } s_i^{x*})$ be the optimal

solution of Model (9) and $(z_{inv}^*, \lambda_j^*, \lambda_{j+1}^*, \text{ and } s_i^{\alpha*})$ be the optimal solution of Model (10). Then, $z_{inv}^* = z_o^*$.

Proof. Given Theorems 4 and 5, it is proved that Models (9) and (14) have similar objective function values. Furthermore, in Theorem 6, we proved that Models (14) and (10) have similar objective function values. As a result, given Theorems 4, 5, and 6, Models (9) and (10) have similar objective function values. ■

3.4. Numeric example

Suppose that there are 8 DMUs, and each DMU has 2 inputs (x_1 and x_2) and 2 outputs (y_1 and y_2). Data are shown in Table 2.

Given input-oriented RAM model (Model 9), Table 3 demonstrates efficiency scores of DMUs and distances of DMU_o from efficient frontier, where s_1^{x*} and s_2^{x*} are distances of DMU_o from efficient frontier for input 1 and input 2, respectively.

Now, Model (13) is utilized and s_1^{x*} and s_2^{x*} are considered to determine α_{io} and Δy_{ro} , where $\alpha_{io} = x_{io} + \Delta x_{io}$. Results are shown in Table 4. Given Model (14) and Table 4, efficiency scores of inverse models are shown in Table 5.

As is seen, the efficiency scores in Tables 3 and 5 are similar, although some outputs have changed, yet inputs remain unchanged.

3.5. The inverse network-dynamic input-oriented RAM model

In a classical approach, a decision-maker changes outputs (inputs) and solves Model (8) for calculating a new set of inputs (outputs). Herein, for the first time, two approaches are proposed:

Approach 1. Given the presented theorems, here, we extend the inverse input-oriented RAM Model (10) to inverse network-dynamic input-oriented RAM model, proposed as follows:

$$\max \quad \frac{1}{T} \sum_{t=1}^T \frac{1}{K} \sum_{k=1}^K \frac{1}{m} \sum_{i=1}^m R_{io k}^{x^t} s_{io k}^{x^t},$$

Table 2. Numeric example dataset.

DMUs	Inputs		Outputs	
	x_1	x_2	y_1	y_2
A	3	5	13	13
B	2	4	12	13
C	5	7	15	15
D	4	6	14	15
E	8	10	18	13
F	9	13	19	17
G	1	2	20	15
H	14	10	11	10

Table 3. Efficiency scores of DMUs.

DMUs	A	B	C	D	E	F	G	H
Efficiency scores	0.7867	0.8706	0.6189	0.7028	0.3672	1	1	0.1363
S_1^*	2	1	4	3	7	0	0	13
S_2^*	3	2	5	4	8	0	0	8

Table 4. Results of Model (13).

DMUs	Changes in inputs		Changes in outputs	
	Δx_{1o}	Δx_{2o}	Δy_{1o}	Δy_{2o}
A	0	0	7	2
B	0	0	8	2
C	0	0	5	0
D	0	0	6	0
E	0	0	2	2
F	0	0	0	0
G	0	0	0	0
H	0	0	9	5

s.t.:

$$\sum_j^n x_{ijk}^t \lambda_{jk}^t + s_{io}^t = x_{io}^t, \quad i = 1, \dots, m,$$

$$\forall K, T,$$

$$\sum_j^n y_{rjk}^t \lambda_{jk}^t \geq y_{ro}^t, \quad r = 1, \dots, p,$$

$$\forall K, T,$$

$$\sum_j^n l_{wj(k-h)}^t \lambda_{jk}^t = \sum_j^n l_{wj(k-h)}^t \lambda_{jh}^t,$$

$$w = 1, \dots, W, \quad \forall K, T,$$

$$\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t \geq c_{uo}^{t,t+1},$$

$$u = 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K,$$

$$\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t = \sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^{t+1},$$

$$u = 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K,$$

$$\sum_j^n \lambda_{jk}^t = 1, \quad \forall K, T,$$

$$\lambda_{jk}^t, s_{io}^t \geq 0, \quad \forall i, j, r. \quad (26)$$

Tone and Tsutsui [13] classified intermediate measures into four categories: free, fixed (non-discretionary), input intermediate, and output intermediates. In addition, they classified carry-overs into four categories: good, bad, free, and fixed carry-overs. Model (26) demonstrates a case with fixed intermediate measures and good carry-overs. The third set of constraints of Model (26) connects two divisions. Moreover, the fifth set of constraints of Model (26) links two consecutive terms. Given Tone and Tsutsui [13] classification, good carry-overs play a role of outputs. As a result, in Model (26), we have good carry-overs addressed in the fourth set of constraints.

Model (27) is a multi-objective linear programme. It determines α_{io}^t , Δy_{ro}^t , and $\Delta c_{uo}^{t,t+1}$, where $(\alpha_{io}^t = x_{io}^t + \Delta x_{io}^t)$. The optimal solution of Model (27) is $(\alpha_{io}^{t*}, \Delta y_{ro}^{t*}, \Delta c_{uo}^{t,t+1*}, \text{ and } \lambda_{jk}^{t*})$.

$$\min \quad \alpha_{io}^t,$$

s.t.:

$$\sum_j^n x_{ijk}^t \lambda_{jk}^t + s_{io}^{t*} = \alpha_{io}^t, \quad i = 1, \dots, m,$$

$$\forall K, T,$$

$$\sum_j^n y_{rjk}^t \lambda_{jk}^t = y_{ro}^t + \Delta y_{ro}^t, \quad r = 1, \dots, p,$$

$$\forall K, T,$$

$$\sum_j^n l_{wj(k-h)}^t \lambda_{jk}^t = \sum_j^n l_{wj(k-h)}^t \lambda_{jh}^t,$$

$$w = 1, \dots, W, \quad \forall K, T,$$

Table 5. Efficiency scores of inverse models.

DMUs	A	B	C	D	E	F	G	H
Efficiency scores	0.7867	0.8706	0.6189	0.7028	0.3672	1	1	0.1363

$$\begin{aligned}
\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t &= c_{uok}^{t,t+1} + \Delta c_{uok}^{t,t+1}, \\
u &= 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K, \\
\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t &= \sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^{t+1}, \\
u &= 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K, \\
\alpha_{iok}^t &\geq x_{iok}^t, \quad i = 1, \dots, m, \quad \forall K, T, \\
\sum_j^n \lambda_{jk}^t &= 1, \quad \forall K, T, \\
\lambda_{jk}^t &\geq 0, \quad \Delta y_{rok}^t, \Delta c_{uok}^{t,t+1} : \text{free}, \quad \forall i, j, r, t. \quad (27)
\end{aligned}$$

Model (27) minimizes inputs and determines changes of normal outputs, intermediate outputs, and good carry-overs. Expression $\alpha_{iok}^t \geq x_{iok}^t$ does not let the inputs be decreased to less than original inputs. Thus, Models (26) and (28) have similar input ranges ($R_{iok}^t = R_{iok}^{t*}$). Finally, inverse network-dynamic input-oriented RAM model is as follows:

$$\begin{aligned}
\max \quad & \frac{1}{T} \sum_{t=1}^T \frac{1}{K} \sum_{k=1}^K \frac{1}{m} \sum_{i=1}^m R_{iok}^{\alpha^{t*}} s_{iok}^{\alpha^t}, \\
\text{s.t.:} \quad & \\
\sum_j^n x_{ijk}^t \lambda_{jk}^t + \alpha_{iok}^{t*} \lambda_{(n+1)k}^t + s_{iok}^{\alpha^t} &= \alpha_{iok}^{t*}, \\
i &= 1, \dots, m, \quad \forall K, T, \\
\sum_j^n y_{rjk}^t \lambda_{jk}^t + (y_{rok}^t + \Delta \bar{y}_{rok}^t) \lambda_{(n+1)k}^t &\geq y_{rok}^t + \Delta y_{rok}^{t*}, \\
r &= 1, \dots, p, \quad \forall K, T, \\
\sum_j^n l_{wj(k-h)}^t \lambda_{jk}^t + l_{wj(k-h)}^t \lambda_{(n+1)k}^t &= \sum_j^n l_{wj(k-h)}^t \lambda_{jh}^t \\
&+ l_{wj(k-h)}^t \lambda_{(n+1)h}^t, \\
w &= 1, \dots, W, \quad \forall K, T, \\
\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t + (c_{uok}^{t,t+1} + \Delta c_{uok}^{t,t+1*}) \lambda_{(n+1)k}^t &\geq c_{uok}^{t,t+1} + \Delta c_{uok}^{t,t+1*}, \\
u &= 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K,
\end{aligned}$$

$$\begin{aligned}
\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t + (c_{uok}^{t,t+1} + \Delta c_{uok}^{t,t+1*}) \lambda_{(n+1)k}^t &= \sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^{t+1} + (c_{uok}^{t,t+1} + \Delta c_{uok}^{t,t+1*}) \lambda_{(n+1)k}^{t+1}, \\
u &= 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K, \\
\sum_j^n \lambda_{jk}^t + \lambda_{(n+1)k}^t &= 1, \quad \forall K, T, \\
\lambda_{jk}^t, \lambda_{(n+1)k}^t, s_{iok}^{\alpha^t} &\geq 0, \quad \forall i, j, r. \quad (28)
\end{aligned}$$

Given the inverse oriented-RAM (Model (10)), only two types of variables, including intermediate measures and carry-overs, are added to Model (28). Intermediate measures and carry-overs do not have direct impact on objective function.

Approach 2. Given Model (27), we propose Model (29). Inputs and outputs are changed simultaneously. In Model (29), despite Model (27), inputs can be reduced to their lower bounds and be increased to their upper bounds. Expression $\underline{x}_{iok}^t \leq x_{iok}^t + \Delta x_{iok}^t \leq \bar{x}_{iok}^t$ guarantees input ranges to remain unchanged. Also \underline{x}_{iok}^t and \bar{x}_{iok}^t are lower and upper bounds of inputs, respectively.

$$\begin{aligned}
\min \quad & \Delta x_{iok}^t, \\
\text{s.t.:} \quad & \\
\sum_j^n \underline{x}_{ijk}^t \lambda_{jk}^t + s_{iok}^{x^{t*}} &= x_{iok}^t + \Delta x_{iok}^t, \quad i = 1, \dots, m, \\
& \forall K, T, \\
\sum_j^n y_{rjk}^t \lambda_{jk}^t &= y_{rok}^t + \Delta y_{rok}^t, \quad r = 1, \dots, p, \\
& \forall K, T, \\
\sum_j^n l_{wj(k-h)}^t \lambda_{jk}^t &= \sum_j^n l_{wj(k-h)}^t \lambda_{jh}^t, \\
w &= 1, \dots, W, \quad \forall K, T, \\
\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t &= c_{uok}^{t,t+1} + \Delta c_{uok}^{t,t+1}, \\
u &= 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K, \\
\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t &= \sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^{t+1},
\end{aligned}$$

$$\begin{aligned}
u &= 1, \dots, U, \quad t = 1, \dots, T-1, \quad \forall K, \\
\bar{x}_{io k}^t &\leq x_{io k}^t + \Delta x_{io k}^t \leq \bar{x}_{io k}^t, \\
i &= 1, \dots, m, \quad \forall K, T, \\
\sum_j^n \lambda_{jk}^t &= 1, \quad \forall K, T, \\
\lambda_{jk}^t &\geq 0, \quad \Delta x_{io k}^t, \Delta y_{ro k}^t, \Delta c_{uok}^{t,t+1} : \text{free}, \quad \forall i, j, r, t.
\end{aligned} \tag{29}$$

4. Case study

Nirou Moharekeh Industrial Co. (NMI) is an Iranian manufacturer that manufactures spare parts such as different types of gear boxes, splines, and shafts. NMI delivers them to Iran Khodro (an Iranian automaker). NMI has 12 suppliers that provide gear boxes. Dataset is shown in Table 6, which dates back to 2010-2015. Suppliers provide required spare parts of NMI Co. Figure 4 shows the structure of supply chain.

In this paper, we focus on suppliers of NMI Co. Each supplier of NMI has three divisions (see Figure 5). Each division has three inputs (including wage cost, energy cost, and material cost (economic factors)), two good carry-overs (including green programs and ISO

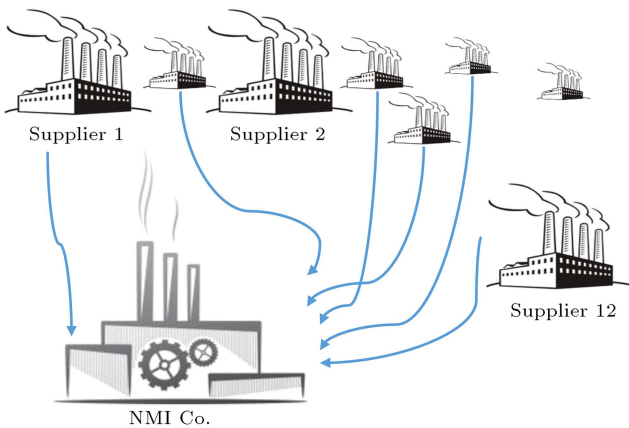


Figure 4. Overall structure of supply chain of NMI.

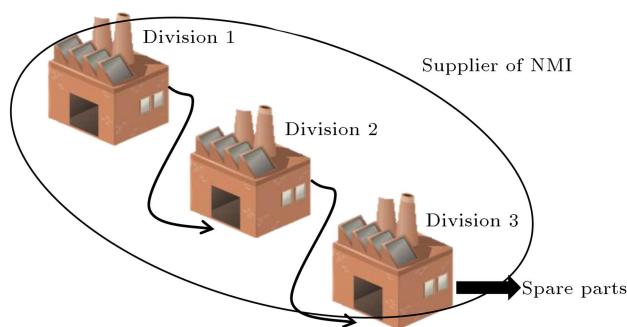


Figure 5. Internal structure of each supplier of NMI.

TS (environmental factor)), and human care programs (social factor). In addition, each division has one fixed intermediate measure (intermediate product) (see Figure 6). First, divisions have only two inputs including wage cost and energy cost.

Figure 6 depicts divisions, inputs, carry-overs, and intermediate measure of the j th supplier of NMI during 6 years. The following notations are defined:

- x_{ijk}^t The i th input of the j th DMU in the k th division in term t ;
- $l_{wj(k-h)}^t$ The w th ($w = 1, \dots, W$) intermediate measure of the j th DMU which is sent from the k th division to the h th division in term t ;
- $c_{ujk}^{t,t+1}$ The u th ($u = 1, \dots, U$) carry-over of the j th DMU in the k th division from term t to term $t+1$.

First, DMUs' efficiency scores are calculated in 6 years (terms). Given Table 6, there are huge differences between the smallest and biggest values in inputs (big ranges). Thus, our new (Model (30)) can be used.

$$\max \quad \frac{1}{T} \sum_{t=1}^T \frac{1}{K} \sum_{k=1}^K \frac{1}{m} \sum_{i=1}^m R_{io k}^{x^t} s_{io k}^{x^t},$$

s.t.:

$$\sum_j^n x_{ijk}^t \lambda_{jk}^t + s_{io k}^{x^t} = x_{io k}^t, \quad i = 1, \dots, m,$$

$$\forall K, T,$$

$$\sum_j^n l_{wj(k-h)}^t \lambda_{jk}^t = \sum_j^n l_{wj(k-h)}^t \lambda_{jh}^t,$$

$$w = 1, \dots, W, \quad \forall K, T,$$

$$\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t \geq c_{uok}^{t,t+1}, \quad u = 1, \dots, U,$$

$$t = 1, \dots, T-1, \quad \forall K,$$

$$\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t = \sum_j^n c_{ujk}^{t+1,t+1} \lambda_{jk}^{t+1}, \quad u = 1, \dots, U,$$

$$t = 1, \dots, T-1, \quad \forall K,$$

$$\sum_j^n \lambda_{jk}^t = 1, \quad \forall K, T,$$

$$\lambda_{jk}^t, s_{io k}^{x^t} \geq 0, \quad \forall i, j, r. \tag{30}$$

Table 6. Dataset*.

	Suppliers (DMUs)											
	TECH. A. T.	STEEL P.	D. L. KARAN	PARS HAM.	FARAZAN	SIRIN S. N.	PIROOZ	ALSAN	KARIN	TIR	BARAN	HAMRAH
Division 1												
Wage	8,635,305,571	1,999,707,195	794,951,857	491,717,007	113,100,561	98,708,866	0	1,007,877,808	299,144,285	238,468,076	259,199,894	0
Energy	31,987,890	64,357,095	33,108,240	12,245,228	1,334,355	2,343,000	0	9,091,335	8,311,875	4,686,000	6,619,635	0
Material	0	0	0	0	0	0	0	0	0	0	0	0
ISO Green	6,925,500	3,000,000	1,500,000	2,940,000	2,850,000	2,550,000	1,350,000	2,880,000	3,600,000	2,535,000	2,760,000	1,350,000
and ISO TS	27,830,250	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100
Human care	390,525	787,165	404,485	149,689	16,297	28,545	0	110,745	101,418	56,976	80,863	0
Intermediate measure												
Division 2												
Wage	20,075,290,095	5,937,128,800	1,727,520,545	1,123,924,587	296,569,872	258,832,276	0	2,048,884,342	719,541,969	614,515,373	612,914,666	0
Energy	511,806,240	1,029,713,520	529,731,840	195,923,640	21,349,680	37,488,000	0	145,461,360	132,990,000	74,976,000	105,914,160	0
Material	6,197,503,577	10,336,941,152	11,344,526,256	2,551,443,820	0	682,685,080	0	5,044,580,800	3,915,134,424	682,685,080	760,085,600	0
ISO Green	9,234,000	4,000,000	2,000,000	3,920,000	3,800,000	3,400,000	1,800,000	3,840,000	4,800,000	3,380,000	3,680,000	1,800,000
and ISO TS	27,830,250	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100
Human care	390,525	786,795	404,161	149,685	16,282	28,539	0	110,661	101,334	56,948	80,848	0
Intermediate measure												
Division 3												
Wage	10,642,369,874	2,690,482,931	958,560,399	602,630,617	145,288,159	126,800,692	0	1,190,510,533	372,898,265	304,441,286	321,255,117	0
Energy	95,963,670	193,071,285	99,324,720	36,735,683	4,003,065	7,029,000	0	27,274,005	24,935,635	14,058,000	19,858,905	0
Material	538,913,355	898,864,448	986,480,544	221,864,680	0	59,363,920	0	438,659,200	340,446,472	59,363,920	66,094,400	0
ISO Green	6,925,500	3,000,000	1,500,000	2,940,000	2,850,000	2,550,000	1,350,000	2,880,000	3,600,000	2,535,000	2,760,000	1,350,000
and ISO TS	27,830,250	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100	11,969,100
Human care	387,732	780,086	401,312	148,427	16,174	28,400	0	110,198	100,750	56,800	80,238	0
Intermediate measure												
Division 1												
Wage	9,285,235,307	1,026,619,436	1,159,823,859	1,465,291,441	153,891,064	1,819,894,113	1,882,400	119,326,391	130,488,341	1,287,254,608	269,329,613	191,583,192
Energy	44,084,178	44,804,559	43,836,748	46,358,463	2,497,081	36,219,392	130,909	3,796,688	4,384,634	28,795,184	10,769,091	1,707,158
Material	0	0	0	0	0	0	0	0	0	0	0	0
ISO Green	19,170,000	7,800,000	4,050,000	8,700,000	7,410,000	8,160,000	4,620,000	7,440,000	10,860,000	6,300,000	7,140,000	4,200,000
and ISO TS	379,052,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000
Human care	406,910	414,439	405,754	428,648	23,055	333,817	1,205	34,983	40,452	264,813	99,443	15,780
Intermediate measure												
Division 2												
Wage	21,223,394,988	2,837,657,375	2,520,428,786	3,293,142,713	389,752,272	4,530,282,732	4,707,460	255,004,534	298,259,064	3,375,411,495	615,610,543	460,821,597
Energy	705,346,848	716,872,944	701,387,968	741,735,408	39,953,296	579,510,272	2,094,544	60,747,008	70,154,144	460,722,944	172,305,456	27,314,528
Material	3,955,272,793	8,813,218,016	8,120,457,464	4,360,864,400	1,055,516,294	3,210,501,000	506,912,640	484,232,800	852,138,975	3,210,501,000	11,816,360,400	0
ISO Green	25,560,000	10,400,000	5,400,000	11,600,000	9,880,000	10,880,000	6,100,000	9,920,000	14,480,000	8,400,000	9,520,000	5,600,000
and ISO TS	379,052,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000
Human care	406,666	414,257	405,389	428,369	23,037	333,717	1,205	34,961	40,423	264,704	99,431	15,767
Intermediate measure												
Division 3												
Wage	11,379,649,286	1,344,345,390	1,398,526,478	1,785,967,103	195,270,223	2,295,400,888	2,388,550	143,129,574	159,921,801	1,653,597,922	330,080,653	238,818,000
Energy	132,252,534	134,413,677	131,510,244	139,075,389	7,491,243	108,658,176	392,727	11,390,064	13,153,902	86,385,552	32,307,273	5,121,474
Material	343,936,765	766,366,784	706,126,736	379,205,600	91,784,026	279,174,000	44,079,360	42,107,200	74,099,041	279,174,000	1,027,509,600	0
ISO Green	19,170,000	7,800,000	4,050,000	8,700,000	7,410,000	8,160,000	4,620,000	7,440,000	10,860,000	6,300,000	7,140,000	4,200,000
and ISO TS	379,052,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000	16,302,000
Human care	404,442	411,051	402,172	425,307	22,909	332,288	1,201	34,832	40,226	264,176	98,799	15,662
Intermediate measure												

* All wage costs, energy costs, material costs, ISO Green and ISO TS investments, and human care costs are in Iranian Rial.

Table 6. Dataset* (continued).

	TECH. A. T.	STEEL P.	D. L. KARAN	PARS HAM.	FARAZAN	Suppliers (DMUs)					KARIN	TIR	BARAN	HAMRAH
						SIRIN S. N.	PIROOZ	ALSAN						
2012	Division 1	6,999,013,439	830,938,474	948,546,783	267,313,648	1,139,039,553	148,284,869	0	69,927,244	1,356,621,486	393,955,586	0	0	
		48,644,232	44,163,912	43,508,868	5,966,844	33,415,200	10,464,168	0	3,427,788	36,535,200	8,060,676	0		
		0	0	0	0	0	0	0	0	0	0	0		
		7,695,000	3,130,920	3,492,180	2,974,374	3,275,424	1,854,468	2,986,416	4,359,204	2,528,820	2,865,996	1,685,880		
		30,922,500	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000		
	313,507	285,116	280,988	38,440	215,078	67,232	0	22,070	234,633	51,950	0	0		
	Division 2	16,271,138,033	2,256,595,454	2,131,794,289	713,307,925	2,884,789,034	432,393,692	0	162,565,175	3,263,128,004	885,388,348		0	
		778,307,712	706,622,592	696,141,888	95,469,504	534,643,200	167,426,688	0	54,844,608	584,563,200	128,970,816		0	
		5,149,379,165	5,533,809,476	4,943,969,600	587,710,720	1,844,565,040	344,196,840	0	2,498,484,480	5,245,591,600	3,419,851,600		0	
		10,260,000	4,174,560	4,656,240	3,965,832	4,367,232	2,472,624	3,981,888	5,812,272	3,371,760	3,821,328		2,247,840	
		30,922,500	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000		
	313,350	284,999	280,827	38,413	215,035	67,212	0	22,056	234,551	51,945	0	0		
	Division 3	8,625,701,964	1,081,053,733	1,156,134,065	345,558,258	1,445,311,392	198,128,522	0	86,179,513	1,691,096,314	480,171,860		0	
		145,932,696	132,491,736	130,526,604	17,900,532	100,245,600	31,392,504	0	10,283,364	109,605,600	24,182,028		0	
		447,772,101	481,200,824	429,910,400	51,105,280	160,396,960	29,930,160	0	217,259,520	456,138,400	297,378,400		0	
7,695,000		3,130,920	3,492,180	2,974,374	3,275,424	1,854,468	2,986,416	4,359,204	2,528,820	2,865,996	1,685,880			
30,922,500		13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000			
311,822	283,102	288,744	38,249	214,200	67,078	0	21,973	234,200	51,671	0	0			
Division 1	5,157,263,899	2,959,889,401	757,676,459	16,069,483	2,674,975,796	5,210,744	0	25,569,146	314,896,612	0		221,814,989		
	45,944,054	55,998,367	58,595,338	512,680	68,966,146	595,539	0	1,562,103	13,533,823	0		3,443,223		
	0	0	0	0	0	0	0	0	0	0		0		
	7,695,000	3,130,920	1,860,000	1,787,100	2,235,000	1,500,000	1,500,000	2,745,000	2,222,700	1,440,000		1,425,000		
	30,922,500	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000			
238,043	290,630	60,608	304,217	2,655	356,861	3,076	0	8,086	69,873	0	17,847	0		
Division 2	12,195,077,064	4,860,293,986	339,636,988	2,057,636,404	43,640,202	6,774,778,648	11,910,272	0	59,442,535	811,466,305	0		515,670,149	
	735,104,867	895,973,870	186,309,734	937,525,408	8,202,882	1,103,458,339	9,528,631	0	24,993,640	216,541,171	0		55,091,571	
	3,697,858,942	5,307,762,992	659,249,920	2,876,448,080	0	3,303,074,160	996,800	0	549,291,520	3,303,074,160	0		2,579,068,752	
	10,260,000	4,174,560	1,840,000	2,480,000	2,382,800	2,980,000	2,000,000	2,000,000	3,660,000	1,920,000	1,900,000			
	30,922,500	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000		
237,924	290,510	60,547	304,044	2,653	356,790	3,075	0	8,081	69,849	0	17,834	0		
Division 3	6,391,967,963	3,293,293,714	199,591,411	985,739,607	20,906,452	3,394,239,454	6,386,100	0	31,511,846	402,014,102	0		273,368,526	
	137,832,163	167,995,101	34,933,075	175,786,014	1,538,040	206,898,439	1,786,618	0	4,686,308	40,601,470	0		10,329,670	
	321,552,951	461,544,608	57,326,080	250,125,920	0	287,223,840	83,200	0	47,764,480	287,223,840	0		224,266,848	
	7,695,000	3,130,920	1,380,000	1,860,000	1,787,100	2,235,000	1,500,000	1,500,000	2,745,000	2,222,700	1,440,000		1,425,000	
	30,922,500	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000	13,299,000		
236,764	288,577	60,007	301,960	2,642	355,404	3,069	0	8,050	69,744	0	17,744	0		

* All wage costs, energy costs, material costs, ISO Green and ISO TS investments, and human care costs are in Iranian Rial.

Table 6. Dataset* (continued).

TECH. A. T.	STEEL P.	D. L. KARAN	PARS HAM.	FARAZAN	SIRIN S. N.	Suppliers (DMUs)					TIR	BARAN	HAMRAH
						PIROOZ	ALSAN	KARIN					
2014													
Division 1													
Wage	3,275,020.758	1,110,990.248	267,122.183	0	23,835,939.828	26,711.219	1,481,194.491	201,268.145	0	368,487.488	0		
Energy	53,264,009	105,019,056	14,524.504	0	139,024,956	2,928.176	25,372.465	8,052.337	0	19,571.934	0		
Material	0	0	0	0	0	0	0	0	0	0	0		
ISO Green	21,300,000	4,140,000	5,580,000	3,300,000	6,705,000	4,500,000	6,000,000	8,235,000	4,500,000	5,100,000	3,000,000		
and ISO TS	40,500,000	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333		
Human care	271,195	536,839	74,200	0	708,341	14,893	129,206	40,975	0	99,651	0		
Intermediate measure													
Division 2													
Wage	11,276,994.552	5,252,131.945	725,428.804	0	50,094,716.775	77,889.017	3,502,493.051	518,653.781	0	886,335.543	0		
Energy	852,224.148	1,680,304.896	232,392.060	0	2,224,399,296	46,850.820	405,959.436	128,837.388	0	313,150.944	0		
Material	8,801,797.363	8,314,573.462	1,420,234.820	0	6,676,079.388	576,254.507	5,707,256.101	16,191,565.760	853,733.283	19,170,076.800	5,112,952.072		
ISO Green	28,400,000	5,520,000	7,440,000	4,400,000	8,940,000	6,000,000	8,000,000	10,980,000	6,000,000	6,800,000	4,000,000		
and ISO TS	40,500,000	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333		
Human care	271,059	536,303	74,158	0	708,199	14,888	129,133	40,950	0	99,641	0		
Intermediate measure													
Division 3													
Wage	4,678,875.809	1,376,973.181	347,526.853	0	28,442,742.801	35,689.780	1,835,808.273	256,949.836	0	459,338.024	0		
Energy	159,792.028	315,057.168	43,573.511	0	417,074.868	8,784.529	76,117.394	24,157.010	0	58,715.802	0		
Material	765,373.684	1,110,924.800	123,498.680	0	580,528.642	50,109.088	496,283.139	1,407,962.240	74,237.677	1,666,963.200	444,604.528		
ISO Green	21,300,000	4,140,000	5,580,000	3,300,000	6,705,000	4,500,000	6,000,000	8,235,000	4,500,000	5,100,000	3,000,000		
and ISO TS	40,500,000	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333	18,113,333		
Human care	270,033	532,416	73,635	0	704,816	14,845	128,631	40,823	0	99,224	0		
Intermediate measure													
Division 1													
Wage	2,526,389.793	742,376.500	505,069.803	0	5,289,447.136	54,653.665	1,346,095	96,673.773	793,398.567	0	162,175.771		
Energy	46,889.535	14,375.361	31,925.817	0	75,431.664	6,692.070	267,960	4,296.138	30,029.076	0	7,968.114		
Material	0	0	0	0	0	0	0	0	0	0	0		
ISO Green	8,550,000	1,950,000	3,510,000	2,910,000	3,960,000	2,700,000	3,840,000	4,560,000	3,750,000	3,300,000	3,150,000		
and ISO TS	35,166,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667		
Human care	203,696	881,577	139,115	0	327,916	29,037	1,164	18,665	130,302	0	34,657		
Intermediate measure													
Division 2													
Wage	8,535,839.392	1,239,074.445	1,371,627.693	0	10,064,771.753	151,067.056	3,076,790	240,651.103	2,193,016.435	0	396,824.952		
Energy	750,232.560	230,005.776	510,813.072	0	1,206,906.624	107,073.120	4,287,360	68,738.208	480,465.216	0	127,489.824		
Material	8,533,341.330	1,222,869.566	4,126,165.358	0	1,818,728.514	639,516.531	3,150,328.860	1,966,827.520	653,907.940	0	3,454,931.200		
ISO Green	11,400,000	2,600,000	4,680,000	3,880,000	5,280,000	3,600,000	5,120,000	6,080,000	5,000,000	4,400,000	4,200,000		
and ISO TS	35,166,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667		
Human care	203,594	880,697	139,036	0	327,850	29,028	1,163	18,654	130,256	0	34,632		
Intermediate measure													
Division 3													
Wage	3,580,679.196	829,516.490	2,991,851.324	0	6,127,223.384	71,568.295	1,649,726	121,932.954	1,038,945.562	0	203,342.294		
Energy	140,668.605	43,126.083	606,682.692	0	226,294.992	20,076.210	803,380	12,888.414	90,087.228	0	23,904.342		
Material	742,029.681	106,336.484	2,955,882.908	0	158,150.306	55,610.133	273,941.640	171,028.480	56,861.560	0	300,428.800		
ISO Green	8,550,000	3,240,000	3,510,000	2,910,000	3,960,000	2,700,000	3,840,000	4,560,000	3,750,000	3,300,000	3,150,000		
and ISO TS	35,166,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667	14,776,667		
Human care	202,985	62,231	138,207	0	326,544	28,970	1,160	18,598	129,996	0	34,494		
Intermediate measure													

*: All wage costs, energy costs, material costs, ISO Green and ISO TS investments, and human care costs are in Iranian Rial.

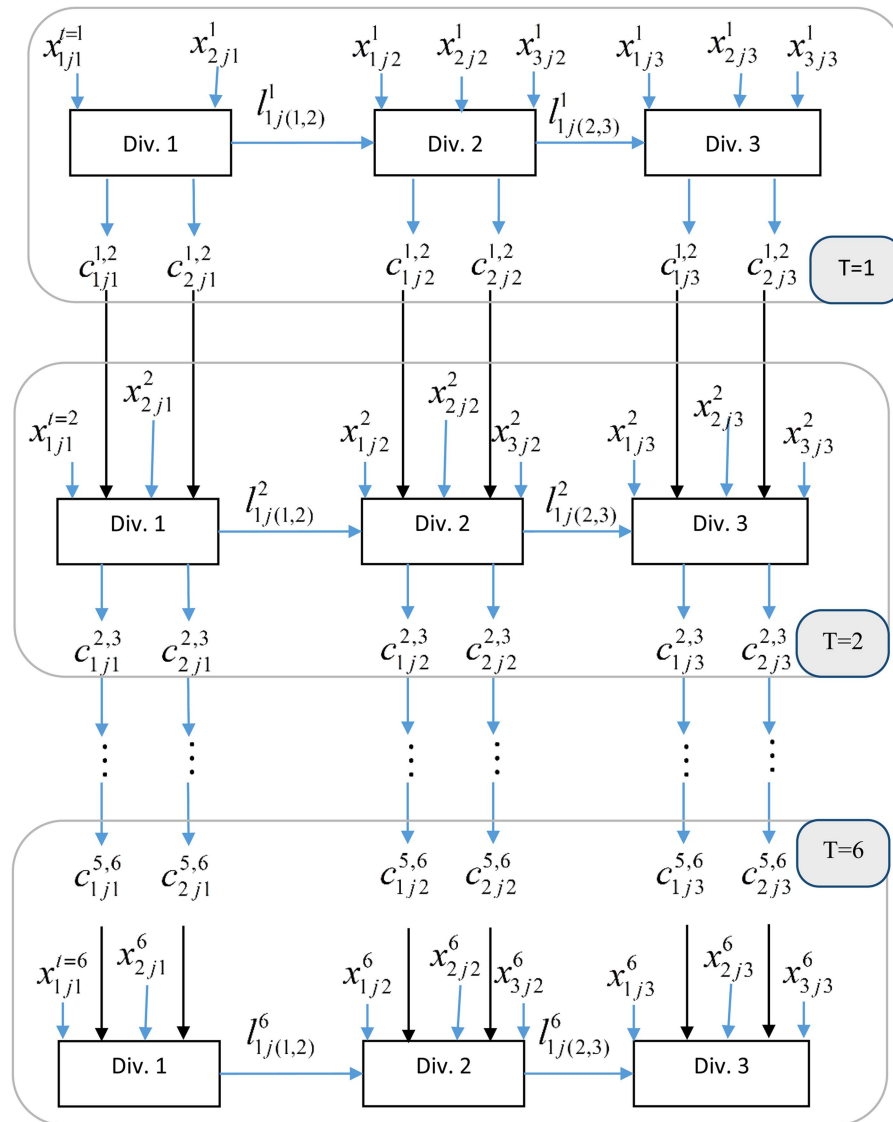


Figure 6. Structure of each supplier of NMI.

Table 7 demonstrates each division's efficiency and efficiency of terms for each supplier of NMI. As is observed in Table 7, DMU D has an increasing trend, while DMU F has a decreasing trend. DMUs A, I, and L are only overall efficient DMUs.

To determine changes of inputs and outputs, the following model is utilized:

$$\min \quad \Delta x_{io k}^t,$$

s. t.:

$$\sum_j^n x_{ijk}^t \lambda_{jk}^t + s_{io k}^{x^t} = x_{io k}^t + \Delta x_{io k}^t,$$

$$i = 1, \dots, m, \quad \forall K, T,$$

$$\sum_j^n l_{wj(k-h)}^t \lambda_{jk}^t = \sum_j^n l_{wj(k-h)}^t \lambda_{jh}^t,$$

$$w = 1, \dots, W, \quad \forall K, T,$$

$$\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t = c_{uok}^{t,t+1} + \Delta c_{uok}^{t,t+1}, \quad u = 1, \dots, U,$$

$$t = 1, \dots, T-1, \quad \forall K,$$

$$\sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^t = \sum_j^n c_{ujk}^{t,t+1} \lambda_{jk}^{t+1}, \quad u = 1, \dots, U,$$

$$t = 1, \dots, T-1, \quad \forall K,$$

Table 7. Efficiency scores.

DMUs (suppliers)	Overall efficiency	Term efficiency						Divisional efficiency		
		2010	2011	2012	2013	2014	2015	Div. 1	Div. 2	Div. 3
TECH. A. T. (A)	1	1	1	1	1	1	1	1	1	1
STEEL P. (B)	0.9974	1	1	0.9846	1	1	1	1	0.9923	1
D. L. KARAN (C)	0.5032	0.5441	0.4403	0.3861	0.9004	0.5501	0.1984	0.5672	0.4716	0.4709
PARS HAM. (D)	0.7047	0.8819	0.5157	0.4542	0.5069	0.9941	0.8758	0.7080	0.7022	0.7040
FARAZAN (E)	0.9999	1	1	0.9999	1	1	1	0.9999	1	1
SIRIN S. N. (F)	0.5396	0.9795	0.5931	0.6245	0.2901	0.2812	0.4691	0.4608	0.5778	0.5802
PIROOZ (G)	0.9999	1	1	1	1	1	0.9999	0.9999	1	1
ALSAN (H)	0.9702	0.8215	1	1	1	1	1	0.9817	0.9648	0.9641
KARIN (I)	1	1	1	1	1	1	1	1	1	1
TIR (J)	0.9206	0.9985	0.7178	0.8746	0.9331	1	1	0.9228	0.9261	0.9130
BARAN (K)	0.8907	0.9459	0.7120	0.7766	1	0.9096	1	0.9555	0.8583	0.8582
HAMRAH (L)	1	1	1	1	1	1	1	1	1	1

$$\sum_j^n \lambda_{jk}^t = 1, \quad \forall K, T,$$

$$\Delta x_{ioK}^t, \lambda_{jk}^t \geq 0, \quad \Delta c_{uok}^{t,t+1} : \text{free}, \quad \forall i, j, r, t. \quad (31)$$

Results of Model (31) are shown in Table 4. Some points can be derived from the results:

- Inputs experience very low changes (Δx_{ijk}^t). Structure of Model (31) addresses this result;
- Manufacturers D. L. KARAN, PARS HAM, SIRIN S. N., and TIR have bigger changes in carry-overs ($\Delta c_{uok}^{t,t+1}$);
- Given DMU TIR, it can be found that DMUs with higher efficiency score may have more changes;
- Carry-overs have large changes. Positive changes of carry-overs imply DMUs' shortfall in investments in green programs, ISO TS programs, and human care programs. Conversely, negative changes imply excess investments.

5. Managerial implications

Key factors of sustainability of supply chains are economic, environmental, and social factors. Though the amount of investment in sustainability factors demonstrates management attention to sustainability of supply chains, investment in each sustainability factor should be proportionate. For instance, in Table 8, given results of PARS HAM, we conclude disproportionate investment.

Amount of investment in green programs and ISO TS is more than that of investment in human care programs. Negative carry-over changes indicate excess

amounts of investment in green programs and ISO TS. Furthermore, PARS HAM has unbalanced investment in green programs during 6 years. On the other hand, positive changes of carry-over (human care programs) imply shortfall of investment in human care programs. Accordingly, the main finding of the case study is to know whether or not the investment of an organization is proportionate.

6. Conclusions

As Seuring and Muller [65] addressed, sustainable supply chain is a growing topic. Carbone et al. [66] argued that a couple of factors triggered companies to apply sustainability principles. Those factors included regulations, scandals, competitors' moves, and customer expectations. Wittstruck and Teuteberg [67] introduced House of Sustainable Supply Chain that had three pillars including environmental performance, economic performance, and social performance. Li [68] claimed that benefits of sustainability, including economic, environmental, and social benefits, should be achieved, simultaneously.

In this paper, a model was proposed to assess sustainability of supply chains. For the first time, we introduced inverse network and dynamic model based upon input-oriented RAM model. As mentioned earlier, RAM model is a unit and translation invariant DEA model. We discussed that the classical inverse DEA models could only determine input or output changes. For the first time, two approaches were proposed to determine input and output changes. The first approach was used to determine which inputs and carry-overs, as well as to what extent, should be changed. In the second approach, inputs can be reduced to their

Table 8. Results of Model (31).

	ΔX^* and ΔC^*	Suppliers (DMUs)											
		TECH. A. T.	STEEL P.	D. L. KARAN	PARS HAM.	FARAZAN	SIRIN S. N.	PIROOZ	ALSAN	KARIN	TIR	BARAN	HAMRAH
2010	Div. 1	DW ¹	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DEN ¹	-0.745E-8	0.0	0.0	0.0	1.970156	0.0	0.0084704	0.0	0.0	1.160656	0.0
		DCARGR-TS ²	-0.186E-8	0.0	-4407.17	-1004242	-0.433E-7	105469.2	0.0	-0.181928	-0.222E-6	187368.8	-103.3697
		DCARHC ³	-0.745E-8	0.0	-0.475E-8	-0.104E-8	0.305874	99.02449	0.0	0.0	0.526E-7	0.186E-8	0.0
	Div. 2	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DEN	-0.103E-7	0.0	0.0	0.0	0.0	0.0	36.1752	0.0	0.0	19.72798	0.0
		DM ⁴	0.0	0.0	3781.88	0.0	0.0	26.13003	0.0	0.0	0.0	264.9410	0.0
		DCARGR-TS	0.332E-8	0.0	-3.0411	-88519.5	0.0	145506.2	0.0	-0.116260	0.521E-7	-2.026985	-0.873759
		DCARHC	-0.213E-8	0.0	0.37488	167730.6	0.0	0.0	-0.364701	-0.141E-8	-0.555666	0.0091881	0.0
	Div. 3	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DEN	0.0	0.0	0.0	0.0	0.483685	-0.288E-7	3.04067	0.0	0.0	0.0	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	16.20219	0.0
		DCARGR-TS	-0.171E-8	0.0	-22.523	-67875.2	0.0	109051.2	0.0	-0.080657	-0.791E-8	0.411475	0.0516349
2011	Div. 1	DCARHC	-0.325E-8	0.0	0.141E-8	167600.4	0.0	8.871403	0.0	-0.016989	-0.707E-7	1.382778	0.262E-8
		DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.39747	0.0	0.0
		DCARGR-TS	0.0	0.0	968808.1	-2660908	-0.795E-7	80279.25	0.0	-0.214151	-0.932E-6	2077114.	300000
		DCARHC	0.0	0.0	0.137E-8	0.0	0.108E-6	2264.724	0.0	0.141E-8	-0.109E-5	0.345E-8	0.0
	Div. 2	DW	0.0	0.0	0.0	0.0	0.0	392.8517	0.0	0.0	0.0	0.0	0.0
		DEN	0.0	0.0	0.0	0.0	0.0	186.9409	0.0	0.0039664	0.0	0.0	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DCARGR-TS	0.0	0.0	1314663.0	-260899.8	0.0	120860.2	0.0	-0.299907	0.0	1720426.	399993.9
		DCARHC	0.0	0.0	8.57366	3836057.0	0.186E-8	-0.186E-8	0.0	-0.492839	0.0	-12.7082	0.210135
	Div. 3	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	114.9616	0.0
		DEN	0.0	0.0	30.8368	0.0	0.0	0.0	0.0	0.0	4.033516	6.212341	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DCARGR-TS	0.0	0.0	985936.7	-200734.2	0.0	90172.23	0.0	-0.177334	0.186E-8	1575897.	299999.8
		DCARHC	0.0	0.0	0.321E-7	3833079.0	0.175E-8	202.8921	0.0	-0.388562	-0.170E-5	31.62460	0.0139E-8
2012	Div. 1	DW	0.0	0.0	77.5122	0.0	0.0	0.0	0.0	0.0	0.0	28.28630	0.0
		DEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.937587	0.0
		DCARGR-TS	0.0	0.0	388879.6	-1068089	-0.313E-7	32224.09	0.0	-0.085960	-0.373E-6	833753.7	120420.0
		DCARHC	0.0	0.0	0.0	-0.372E-8	0.512E-8	110.0272	0.0	0.0	-0.886E-6	0.0	0.0
	Div. 2	DW	0.0	141.0	0.0	0.0	0.0	249.0799	0.0	-0.302E-7	0.0	0.0	0.0
		DEN	0.0	0.0	24.7075	0.0	0.0	0.0	0.0	-0.302E-7	0.0	0.0	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.302E-7	0.0	0.0	433.8932
		DCARGR-TS	0.0	0.0	527413.5	-105153.8	0.0	48003.31	0.0	-0.120356	0.0	691015.0	159997.6
		DCARHC	0.0	0.0	0.41653	186367.3	0.0	0.0	0.0	-0.402053	0.0	-0.617406	0.010209
	Div. 3	DW	0.0	0.0	519.468	0.0	0.0	0.0	-0.298E-7	-0.238E-7	0.0	0.0	58.75217
		DEN	0.0	0.0	17.9930	0.0	0.0	0.0	0.0	-0.238E-7	0.0	0.0	5.812746
		DM	0.0	0.0	0.0	0.0	0.0	0.0	-0.372E-8	-0.238E-7	0.0	0.0	3.681721
		DCARGR-TS	0.0	0.0	395664.7	-80762.99	0.0	36253.35	0.0	-0.071172	0.0	632986.4	120999.9
		DCARHC	0.0	-0.158E-8	0.242E-7	186222.6	0.0	9.857115	0.0	-0.316984	0.208E-8	1.536419	0.0
2013	Div. 1	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DCARGR-TS	0.0	0.185E-8	121642.0	-281791.8	-202600.0	-418299.0	0.0	0.0428301	-0.212E-6	0.0077834	60000.0
		DCARHC	0.0	-0.276E-8	-0.110E-8	-0.372E-8	0.558E-8	110.0272	0.0	0.0	-0.886E-6	0.149E-8	0.0
	Div. 2	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.2491E-4	0.0	0.0	0.0	0.0
		DEN	0.0	0.0	0.0	0.0	0.0	0.0	0.1992E-4	0.0	0.0	0.0	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.1973E-5	0.0	0.0	-0.023E-8	0.0
		DCARGR-TS	-0.186E-8	-0.341E-7	270268.8	106528.3	0.0	-130917.9	0.0	-0.604637	0.0	0.0679126	79998.78
		DCARHC	-0.372E-8	0.608E-8	0.41653	186367.3	0.0	0.00	0.0	-0.402053	0.0	-0.617406	0.010209
	Div. 3	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.684E-7	0.0	0.0	0.0	0.0
		DEN	0.0	0.0	0.0	14.005	0.0	0.0	0.0	0.0	8.883	0.0	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DCARGR-TS	-0.643E-8	0.0	202841.0	78873.71	0.0	-186631.4	0.0	-0.035753	0.0	0.2064502	59999.96
		DCARHC	-0.340E-7	-0.186E-8	0.0	186222.6	0.0	9.857115	0.0	-0.316984	0.0	1.536419	0.0

1. DW and DEN denote changes of wage and energy costs; 2. DCARGR-TS denotes changes of green programs and ISO TS investments;

3. DCARHC denotes changes of human care programs costs; 4. DM represents changes of material costs.

Table 8. Results of Model (31) (continued).

		ΔX^* and ΔC^*	Suppliers (DMUs)											
			TECH. A. T.	STEEL P.	D. L. KARAN	PARS HAM.	FARAZAN	SIRIN S. N.	PIROOZ	ALSAN	KARIN	TIR	BARAN	HAMRAH
2014	Div. 1	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.172E-8	0.0	0.0
		DEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.172E-8	0.0	0.0
		DCARGR-TS	0.0	-0.242E-7	-29139.9	-845375.4	0.0	-2536489.	0.0	-0.107932	-0.613E-6	0.0151980	-284737.7	0.0
		DCARHC	0.0	0.288E-8	1.99375	-0.465E-8	-0.186E-8	139.7647	0.0	-0.022961	0.134E-6	0.0312679	0.012968	0.0
	Div. 2	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.464E-7	0.0	0.0
		DEN	0.0	0.0	395.657	0.0	-0.498E-8	0.0	0.0	0.0	0.0	-0.464E-7	0.0	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DCARGR-TS	0.0	0.271E-6	18142.27	-129411.1	0.0	-1002170.	0.0	-0.232607	0.135E-5	0.2455036	-1061060.	0.0
		DCARHC	0.0	0.623E-8	0.529113	236737.5	0.0	-0.815E-8	0.0	-0.510718	-0.171E-8	-0.840912	0.012968	0.0
	Div. 3	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.115E-6	0.0	0.0
		DEN	0.0	0.0	100.307	0.0	0.0	0.0	0.0	0.0	0.0	0.115E-6	0.0	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DCARGR-TS	-0.674E-6	0.0	13628.13	-996953.6	0.0	-1471328.	0.0	-0.158647	0.119E-6	0.3812455	-795185.9	0.0
		DCARHC	0.0	-0.295E-8	0.0	236553.7	0.0	12.52123	0.0	-0.431735	0.0	2.092614	-0.186E-8	0.0
Div. 1	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	DEN	0.0	0.0	41.1759	0.0	0.0	0.0	0.0	0.5732829	0.0	0.0	0.0	0.0	
	DCARGR-TS	0.0	-0.390E-8	1135687.0	-284467.6	0.0	-973915.	458334.1	-0.068623	-0.232E-6	0.0024823	-61693.16	-0.201E-7	
	DCARHC	0.0	0.401E-6	1.81593	0.0	0.0	127.2990	0.209E-4	-0.209136	0.121E-6	0.0284792	0.0105793	0.0	
2015	Div. 2	DW	0.0	0.0	19.8118	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DEN	0.0	0.0	43.5999	0.0	0.0	0.0	0.0	9.190957	0.0	0.0	0.0	0.0
		DM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		DCARGR-TS	0.0	-0.114E-6	1526598.0	-127922.6	0.0	-217139.3	0.0	-0.151619	0.121E-6	-0.164971	-229896.4	-0.201E-7
		DCARHC	0.0	0.0	0.43164	215622.9	0.0	-0.279E-8	0.0	-0.416618	0.291E-8	-0.630291	0.0105793	0.0
Div. 3	DW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.543818	0.0	0.0	0.0	0.00	
	DEN	0.0	0.0	21.5113	0.0	0.0	0.0	0.0	1.723376	0.0	0.0	0.0	0.0	
	DM	0.0	0.0	101.675	0.0	0.0	0.0	0.0	0.0	0.0	0.447E-7	0.0	0.0	
	DCARGR-TS	0.170E-8	0.0	1144953.0	-70833.57	0.0	-632645.1	0.0	-0.101078	0.551E-7	0.336189	-172290.3	0.0	
	DCARHC	0.568E-8	-0.327E-8	-0.407E-8	215455.5	0.0	11.40446	0.0	-0.352205	0.188E-8	1.707133	0.0	0.0	

1. DW and DEN denote changes of wage and energy costs; 2. DCARGR-TS denotes changes of green programs and ISO TS investments;

3. DCARHC denotes changes of human care programs costs; 4. DM represents changes of material costs.

lower bounds and be increased to their upper bounds. In the first approach, inputs cannot decrease to less than their current values. Negative or positive changes in inputs/outputs demonstrate the direction of future investments. This paper assessed sustainability of supply chains. For prospective researchers, we suggest running our model in fields of assessing production lines, assessing electricity transfer lines, etc.

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Biographies

Majid Kalantary received his BS degree from the Department of Industrial Management at Islamic Azad

University, Karaj, Iran. He obtained his MS degree in Industrial Management from Tehran University, Tehran, Iran. He is currently a PhD candidate of Industrial Management at Islamic Azad University, Science and Research Branch, Tehran, Iran. He is a sessional lecturer of the Department of Industrial Management at Islamic Azad University, Karaj Branch, Karaj, Iran. His research interests include data envelopment analysis and multi-criteria decision making.

Reza Farzipoor Saen is a Full Professor of Operations Management at the Department of Industrial Management, Islamic Azad University, Karaj Branch in Iran. Also, he is a Visiting Professor at Nottingham Trent University in UK. Furthermore, he is an Adjunct Professor in Maastricht School of Management in Netherlands. In 2002, he obtained his PhD in Industrial Management from the Islamic Azad University, Science and Research Branch in Iran. He has published over 168 refereed papers in many prestigious journals.

Abbas Toloie Eshlaghy is a Full Professor of Industrial Management at the Department of Industrial Management, Science and Research Branch, Islamic Azad University, Tehran, Iran. Also, he is the Head of Industrial Management Department in Science and Research Branch, Islamic Azad University in Iran. He obtained his PhD in Industrial Management from the Islamic Azad University, Science and Research Branch in Iran. He has published over 97 refereed papers in many journals.