Computational Algorithms and Numerical Dimensions

www.journal-cand.com

Com. Alg. Num. Dim Vol. 2, No. 3 (2023) 136–147.

Paper Type: Original Article

A Proposed Model for the Assessment of Supply Chain Management Using DEA and Knowledge Management

Nasim Ekram Nosratian[1], Mohammad Taghi Taghavi Fard[2,*]

[1] Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran; nasim_nosratian@yahoo.com.

[2] College of Management and Accounting, Allame Tabatabaei University, 1489684511 Tehran, Iran; dr.taghavifard@gmail.com.

Citation:

Ekram Nosratian, N., & Taghavi Fard, M. T. (2023). A proposed model for the assessment of supply chain management using DEA and knowledge management. *Computational algorithms and numerical dimensions, 2*(3), 136-147.

Received: 08/02/2023 Reviewed: 09/03/2023 Revised: 09/04/2023 Accepted: 01/05/2023

Abstract

Supply Chain Management (SCM) is an integrated system of planning and control of materials and information, including suppliers, manufacturers, distributors, retailers, and customers. Chain performance measurement is an important issue in SCM. Also, given that the information plays a key role in improving supply chain performance, the kind and amount of information sharing should be investigated. In this paper, the effect of information sharing on supply chain performance will be evaluated. In this way, 17 different scenarios of information sharing are defined and ranked using the cross-efficiency method. Finally, values for different scenarios using simulations and Rockwell Software Arena V5 are reported. The obtained results show that the proposed model is quite valid and efficient and can be easily applied to real-world cases.

Keywords: Supply chain management, Information sharing, Data envelopment analysis, Cross-efficiency method, Ranking, Simulation.

1 | Introduction

Supply Chain Management (SCM) is defined as the planning, execution, and control of supply chain activities in the most optimized possible case. SCM spans all movement and storage of raw materials, work-in-process inventory, and finished goods from the point of origin to the point of consumption. In other words, SCM is related to the coordination of materials, products, and information flows among suppliers, manufacturers, distributors, retailers, and customers [1].

SCM is an integrated approach for planning and controlling the materials and information that flow from suppliers to end customers. SCM connects inventory management, focusing on operation management, with communication analysis in industrial organizations. The field has taken on immense importance during the past few years. The supply chain includes all the activities related to the movement and conversion of materials from the raw material phase to delivery to the end customers and their related information currents.

Corresponding Author: dr.taghavifard@gmail.com

https://doi.org/10.22105/cand.2023.191008

There are two flows in the product flow; one is the information flow, and the other is the financial resource and credit flow. Several different fields used nowadays for the supply chain are as follows:

- *Supply chain simulation.*
- *Supply chain risk management.*
- *Supply chain tracking.*
- *Supply chain reengineering.*
- *Supply chain advanced planning.*
- *Supply chain project management.*
- *Supply distribution and network management.*
- *Fleet management.*
- *Human resources management.*
- *Information management.*
- *Supply chain information system.*

One of the fundamental parts of any SCM system is information sharing [2]. Many researchers think that if we make the unchanged and updated marketing data accessible in all the nodes of a supply chain, we will reach a monolithic supply chain [3], [4]. By obtaining accessible data and sharing it with other parties within the supply chain, an organization may precipitate the current information in the supply chain, improve the efficiency and impressiveness of the supply chain, and answer the customer's changing demands more rapidly. Therefore, eventually, information sharing can bring competitive advantages for the organization. The information-sharing benefit in SCM is thoroughly considered [5]. In order to improve, decrease inventory costs, and enable the material current, information sharing brings harmony between supply chain procedures. Information sharing results in high rates of supply chain accretion by empowering organizations to make reliable transfers and present products to the market swiftly [6].

Information sharing affects the supply chain implementation with regard to service rate and also total expense [7]. According to Lin et al. [8], a higher rate of information sharing is affiliated with a lower total cost, a higher order implement level, and a shorter order cycle time. As information sharing is principal, the importance of its effect on the efficiency of a supply chain pertains to what information is shared, when, and how it is shared [9], [10].

In order to be integrated and various kinds of currents within the overall chain be harmonized, SCM generally needs inter-organizational and intra-organizational relations. By sharing information among dealing partners and coordinating their replenishment and manufacture determinations under request doubt, it can be feasible to reduce expenses and improve customer service rates. Many agents can affect the supply chain efficiency, and the information-sharing agent is the most significant one. Sharing both supply and demand knowledge decreases inventory costs far in make-to-stock or assemble-to-order manufacture. It also substantially decreases order cycle time in an assemble-to-order setting [11].

Some researchers investigated the benefits of sharing customer demand information with members of the supply chain. Bourland et al. [12] analyze the savings in inventory cost that can come off when a manufacturer shares Point-Of-Sale (POS) information with suppliers. Ernst and Kamrad [13] discuss a supply chain in which producers and retailers share demand information and analyze the effect of information sharing on service level. Cachon and Fisher [5] have investigated the value of inventory data and sharing demand. Lee et al. [14] and Cachon and Fisher [5] study the advantages of whacking real-time data on demand and/or inventory levels between suppliers and customers.

Various types of data may be shared in a supply chain, including demand, costs, order information, capacity information, inventory information, etc. Some studies related to demand information sharing are offered here. In order to decrease the bullwhip influence in supply chains, Chen et al. [15] investigated concentrated demand information sharing. Tan [16] evaluated the influence of demand information sharing on supply chain network structures, product structures, and demand hybrids. Lee et al. [14] evaluated the advantages of sharing demand information and discovered some of the drivers by using a two-level supply chain model. Also, Thonemann [17], Zhang et al. [18], Ryu et al. [19], Helper et al. [20], and Cho et al. [21] analyzed the influence of sharing demand information on a supply chain implementation.

Lee et al. [22] have studied why and how inventory information sharing, demand forecasts, orders, and production plans are done. Fiala [23] studies the impact of information sharing on Bullwhip effect, uncertainty reduction, and supply chain performance. Also, Zhou et al. [24] and Wu et al. [25] analyze the effect of information sharing on supply chains.

The companies try to redesign their information-sharing policies to increase profits. Although all the previous studies show the positive effect of information sharing on the supply chain performance, none of them study the influence of different composites of information sharing on the supply chain performance. The article by Yu et al. [26] analyzes this effect.

Yu et al. [26] designed different information-sharing scenarios to analyze the supply chain performance. The desirable indices and also the undesirable ones are necessary in order to measure the performance of each scenario. So, to measure the performance for complete weight flexibility, the usual Data Envelopment Analysis (DEA) model was used.

We have expanded the model proposed by Yu et al. [26] in the present paper so that the supply chain includes 5 sections (supplier, producer, distributor, retailer, and customer). The information to be shared in the chain includes demand information, inventory, capacity, and costs. The last item was added to the above-mentioned paper. These are the innovative aspects of the current paper, which shows how the different composites of information sharing affect the supply chain.

This paper is structured as follows; Section 2 shows the information-sharing scenarios. In Section 3, the solution methodology is explained. The analysis and results are presented in Section 4, and the last section contains the conclusion and future studies.

2 | Proposed Model and Parameters

The extended supply chain model (shown in *Fig. 1*) is a multi-level chain. It is comprised of customers, retailers, distributors, producers, and suppliers, in which the supply and demand values are exchanged between them. In order to study how the way that different composites of information sharing have effects, three scenarios are taken into consideration as follows:

I. No sharing information in which none of the existing information is shared.
II. Partial sharing of information, which may be the following 15 composites:

- *Capacity information sharing (C).*
- *Demand information sharing (D).*
- *Inventory information sharing (I).*
- *Unit Cost of each item information sharing (V).*
- *Production rate information sharing (P).*
- *Demand and capacity information sharing (D&C).*
- *Demand and inventory information sharing (D&I).*
- *Capacity and inventory information sharing (C&I).*
- *Capacity and cost information sharing (C&V).*
- *Demand and cost information sharing (D&V).*
- *Inventory and cost information sharing (I&V).*
- *Capacity and production rate information sharing (C&P).*
- *Demand and production rate information sharing (D&P).*
- *Inventory and production rate information sharing (I&P).*

– *Cost and production rate information sharing (V&P).*

III. Full information sharing in which all the capacity, demand, inventory, cost, and production rate information are shared.

To compare the performance of different scenarios, Rockwell Software Arena V5 is used. The results are shown in *Table 3*.

Input parameters such as initial inventory level, inventory policy, shortage costs, holding costs, order costs, set-up costs, lead times of production and transportation, customer demand rate, and unit production time are shown in *Tables 1* and *2*.

To compare different scenarios, we use 5 performance indexes such as (shown in *Fig. 1*):

I. Total cost (consisting of holding cost, shortage cost, and order cost).
II. Fulfillment rate.
III. Customer service level.
IV. Order cycle time.
V. Waiting time.

Table 1. Initial inventory level and inventory policy.

Inventory	**Retailer 1**	**Retailer 2**	**Distributor 1**	**Distributor 2**	**Manufacturer 1**	**Supplier 1**	**Supplier 2**	**Supplier 3**
Initial inventory level	35	50	145	112	214	240	235	256
Inventory policy (s, S): s	32	25	57	55	69	75	77	81
Inventory policy (s, S): S	46	60	128	129	138	143	150	154

Table 2. Parameters for simulation.

Parameters	**Inputs**
Iteration	40
Simulation time	180 days
Interval distribution of customer order	Exponential distribution (mean = 0.32 day)
Quantity distribution of customer order	Discrete distribution (Q = 2 or 5, Prob. = 0.178; Q = 3 or 4, Prob. = 0.405)
Frequency of replenishment review	Once daily
Transportation lead times	2 (day)
Production lead times	Normal distribution (mean = 0.4 h, standard deviation = 0.05 h)
Unit holding costs	3
Unit shortage costs	7
Order costs	15 (retailers), 30 (distributors), 35 (manufacturers), 40 (suppliers)

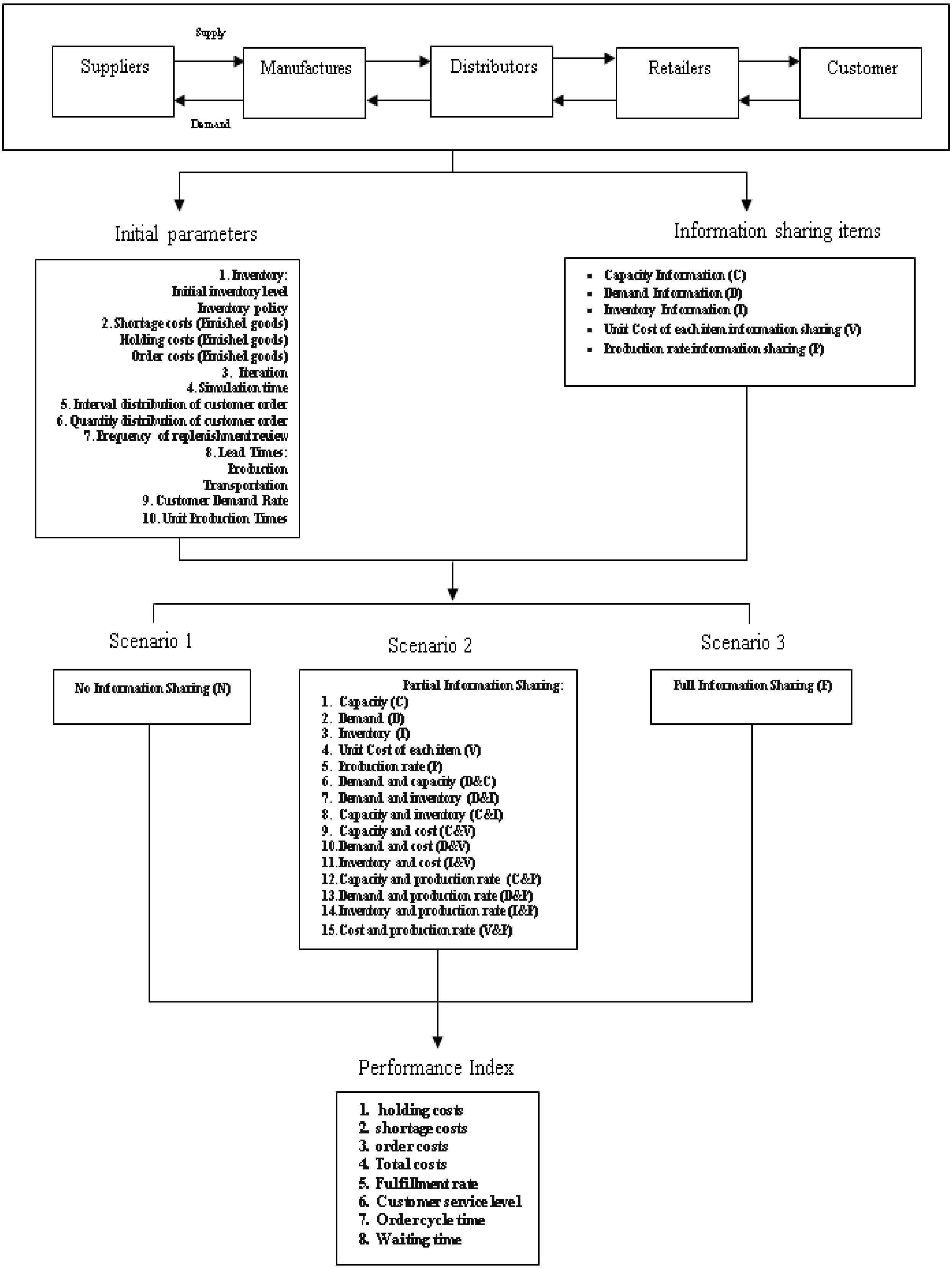

Fig. 1. Supply chain simulation model.

Table 3. Simulation results of performance indices.

Indexes \ Scenario	N	C	D	I	V	P	D&C	D&I	C&I	C&V	D&V	I&V	C&P	D&P	I&P	V&P	F
Shortage costs	220.81	70.12	32.45	101.17	55.78	121.23	23.08	51.98	92.55	67.56	43.27	147.98	133.65	98.32	120.97	64.18	27.11
Holding costs	99.78	302.93	210.06	190.78	265.22	299.11	421.56	278.43	356.99	330.01	247.31	365.04	87.77	129.91	184.23	70.04	480.88
Order cost	160	245	160	160	310	190	245	160	245	135	135	165	245	135	160	135	245
Total costs	480.59	618.05	402.51	451.95	631	610.34	689.64	490.41	694.54	532.57	425.58	678.02	466.42	363.23	465.2	269.22	752.99
Fulfillment rate (%)	64.22	77.24	80.05	70.68	78.01	69.79	79.34	79.04	72.34	70.11	81.76	75.58	69.95	73.72	74.44	80.15	83.23
Customer service level (%)	61.92	73.33	78.85	67.70	72.22	69.90	78.88	75.49	77.90	74.27	79.99	64.63	67.02	69.06	66.61	70.03	84.64
Order cycle time (days)	1.40	1.16	1.02	1.20	1.25	1.36	1.01	1.09	1.19	1.23	1.11	1.21	1.21	1.37	1.24	1.09	1.00
Waiting time (days)	3.27	2.78	2.50	2.66	2.28	2.74	2.33	2.49	2.89	2.81	2.37	2.81	2.51	2.90	2.94	2.49	1.10

3 | Solution Methodology

Regarding the criteria and resulting numbers in *Table 3*, a Multi-Criteria Decision Making (MCDM) problem is introduced. The information-sharing scenarios are our alternatives, and the above-mentioned criteria are our criteria.

In order to evaluate the coordination and information-sharing performance between the supply chain entities in various information-sharing scenarios, this paper brings forward an atypical use of the DEA method. The DEA method was first proposed by Charnes et al. [27] and is identified as an assessment method for performance analysis of different entities. Numerous inputs and outputs distinguish the manufacturing activities of the DEA method. More information on the DEA technique can be found in Boussofiane et al. [28], Charnes et al. [29], and Seiford and Thrall [30].

DEA has become a favorite field in operations research today, and applications entail a broad domain of contexts. The applicability and practicality of DEA may be quickly proved in Cooper et al. [31], [32], and multiple previous studies. The DEA method is used to analyze the performance with numerous inputs and outputs. Therefore, we use this method to assess supply chain information-sharing implementation. In the supply chain, every unit allowed to select the most desirable weights is to be applied to its standings (in this instance, by analyzing the consequent performance scales including fulfillment rate, total cost, customer service level, order cycle time, and waiting time, the various information-sharing scenarios are contrasted) in the normal DEA style.

The contractual DEA model allows full-weight flexibility in the assessment of this simple efficiency mark. By seriously weighing a few desirable inputs and outputs and ignoring the other inputs and outputs entirely, a unit attains a respective efficiency score of 1. With few input/output measures, these kinds of units perform well. So, it is unsuitable to consider the scenarios with an efficiency score of 1 as the candidates with the best synthesis of characteristics. Cook and Kress [33] discuss a design involving an imposed collection of weights that do not supply a just whole evaluation. Nevertheless, the difficulty of selecting the most desirable weights to be used in each unit's standings has still not been removed. The modest efficiency score acquired from Cook and Kress's model is often misleading.

A measure that is more than the simple efficiency score in the decision-making procedure is needed to solve such difficulty. In this part, we present a revision of basic DEA and a cross-efficiency ranking extension to the DEA models and how they may be applied to assess distinct alternative MCDM models.

Imposing a predetermined set of weights on each alternative's standing-by poll organizer is one technique for removing this difficulty. Thus, the composite score, Zi, of alternative i would be given by

$$Z_i = \sum_{j=1}^{k} w_j v_{ij}, \tag{1}$$

where v_{ij} indicates the value of the jth attribute of alternative i ($i = 1,2,\dots\dots,m,\ j = 1,2,\dots\dots,k$), and w_j represents the weight of the jth attribute.

Charnes et al. [27] initially suggested the CCR model. For each DMU, the CCR model tries to determine the optimal weight of the jth attribute of alternative i, w_{ij}, using linear programming so that the composite score Z_{ii}, which is used in the *Objection Function (2)*, is maximized to emphasize that this is alternative i's own evaluation of its desirability.

$$\text{Maximize} \quad Z_{ii} = \sum_{j=1}^{k} w_j v_{ij}, \tag{2}$$

$$\text{Subject to} \quad Z_{ip} = \sum_{j=1}^{k} w_{ij} v_{pj} \le 1, \qquad \text{for all DMUs p; including i.} \tag{3}$$

$$w_{ij} \ge 0, \tag{4}$$

where Z_{ip} denotes cross-efficiency of alternative i's evaluation of alternative p's desirability, i.e., DMU p is evaluated by the weights of DMU i. *Constraints (3)* represent that no alternative p should have a desirability greater than 1 under i's weights.

From one DMU to another, the optimal weights may differ, and each DMU is allocated the best collection of weights with values that may differ from one DMU to another. The weights in DEA, instead of being stabilized ahead, such as given by decision-makers, are the results from the data. Cook and Kress [33] express that each alternative be allowed to offer its weights to maximize its desirability subject to certain rational limitations on the desirability of all the alternatives. Sexton et al. [34] discuss that decision-makers do not always have a rational system for selecting certainty regions. Hence, they suggest using the Cross-Evaluation Matrix (CEM) to rate the alternatives.

In order to defeat the difficulties related to the simple efficiency scores, cross-efficiencies in DEA can usefully be utilized. Cross-efficiencies of a DMU supply data on how well it is acting with the optimal DEA weights of other m-1 DMUs. The cross-efficiencies of all the DMUs can be ordered in a CEM, as shown in *Table 4*. The p^{th} row and ith column of the CEM indicate the cross-efficiency of DMU_p with the optimal weights of DMU_i. The normal simple efficiency evaluations for each DMU are discovered in the leading diagonal of this matrix. The cross-efficiency technique estimates the efficiency score of each DMU_m times using the optimal weights assessed by m LPs.

Table 4. Matrix of cross-efficiencies for m DMUs.

Rating DMU	Rated DMU					
	1	2	3	…	m	Averaged Appraisal of Peer
1	Z_{11}	Z_{12}	Z_{13}	…	Z_{1m}	$\overline{B}_1$
2	Z_{21}	Z_{22}	Z_{23}	…	Z_{2m}	$\overline{B}_2$
3	Z_{31}	Z_{32}	Z_{33}	…	Z_{3m}	$\overline{B}_3$
.	.	.	.		.	.
.	.	.	.	…	.	.
.	.	.	.		.	.
m	Z_{m1}	Z_{m2}	Z_{m3}	…	Z_{mm}	$\overline{B}_m$
Averaged peer-appraisal	$\overline{Z}_1$	$\overline{Z}_2$	$\overline{Z}_3$	…	$\overline{Z}_m$	

Ekram Nosratian and Taghavi Fard | Com. Alg. Num. Dim. 2(2) (2023) 136-147

In the DEA context, in order to rank scale the DMUs, the cross-efficiency ranking method uses the results of the cross-efficiency matrix Zip. It could be argued that $\bar{Z}_i = \sum_{p=1}^{m} Z_{pi}/m$ is more representative than Z_{ii} which is the standard DEA efficiency score since all the elements of the cross-efficiency matrix are investigated, including the diagonal. Since each standard DEA score uses different weights, the standard DEA score, Z_{ii}, is non-analogous, and since $\bar{Z}_i$ uses the weights of all units identically, it is analogous.

When multiple optimum solutions exist, the optimal weights obtained from their model may not be unique, which is a limitation of the CEM evaluated by Sexton et al. [34] model weights. This ambiguity can be solved by using formulations categorized as aggressive and benevolent approaches, which were proposed by Doyle and Green [35], and they not only maximize the efficiency of the target DMU but also take a second goal into account. In the case of aggressive formation, the second goal is minimizing the efficiency of the composite DMU constructed from other m-1 DMUs.

The aggressive formulation is shown below:

$$\text{Maximize} \quad \sum_{j=1}^{k} w_{ij} \sum_{p=1,p\neq i}^{m} v_{pj}, \tag{5}$$

$$\text{Subject to} \quad Z_{ip} \leq 1, \quad \text{for all DMUs } i \neq p. \tag{6}$$

$$\sum_{j=1}^{k} w_{ij}.\, v_{ij} - Z_{ii} = 0, \tag{7}$$

$$w_{ij} \geq 0, \tag{8}$$

where DMU i is the target DMU, $\sum_{j=1}^{k} w_{ij} \sum_{p=1,p\neq i}^{m} v_{pj}$ is the weighted attributes of composite DMU, and Z_{ii} is the simple efficiency of DMU i obtained from usual DEA.

When Z_{ii} it is obtained, as well as solving aggressive *Models (5)-(8)* for alternative i, we are also supplied with values Z_{ip} that may be supposed as assessments of p's desirability from i's standpoint in this modeling framework. The values acquired in a full run of the model can be arranged in a matrix Z in which the values down a column $p(Z_{.p})$ indicate how alternative p is estimated by all alternatives, and values across a row $i(Z_{.i})$ indicate how alternative i evaluates all alternatives. Therefore, this matrix is the abstract of a self- and peer-evaluation process in which on-diagonal elements indicate self-evaluations and off-diagonal elements denote peer-evaluations.

Sexton et al. [34] offered the column averages of Z as appropriate entire rankings of the alternatives. Each alternative is accorded a weight of 1/m in specifying any alternative's overall rating.

4 | Results

Seventeen scenarios and five criteria (performance measures) are introduced in this article. The 5 performance measures include six minimizing criteria (holding cost, shortage cost, order cost, total cost, order cycle time, and waiting time). The remaining criteria (fulfillment rate, customer service level) are defined as the maximizing criteria. The data for this study are shown in *Table 3*.

Models (2) to *(4)* are initially used to obtain the simple efficiency of all SCM information-sharing scenarios. The standard DEA identified scenarios N, D, I, V, D&I, D&V, D&P, and F to be efficient with a relative efficiency score of 1. The rest of the scenarios (C, P, D&C, C&I, C&V, I&V, C&P, I&P, and V&P) obtained an efficiency score of less than 1. However, since our main interest is in finding the best SCM information sharing rather than a group of projects to make up a program, an aggressive approach may be regarded as an appropriate one in this context.

Hence, simple efficiency scores are used in aggressive *Models (5)-(8)* to get the optimal attribute weights for each scenario. These weights also reduce the comparative performance of the compound scenarios, which are built from the remaining m-1 scenarios for each case. Such a matrix and overall rating are shown in

Ekram Nosratian and Taghavi Fard| Com. Alg. Num. Dim. 2(2) (2023) 136-147

Table 5. This table obviously shows that the scenarios F, D, V, D&C, V&P, and D&V have several high cross-efficiency values. Some of the simple, efficient scenarios, such as C, I&P, C&P, and D&P, have several low cross-efficiency values. The adjusted weighted column means of the Z matrix can be used to differentiate among the overall efficient scenarios effectively.

Scenario D&C, which was inefficient with a relative efficiency score of 0.986 and a mean score of 0.903, is rated as a better overall performer than efficient scenario F. Therefore, this technique lets the decision maker rate the SCM information-sharing scenarios based on their entire efficiency.

Demand information reinforces, postpones, and swings from downstream to upstream along the supply chain [14]. This information is significant and essential to supply chain partnerships. In addition, since demand information directly affects manufacturing scheduling, inventory control, and delivery plans, it has a significant influence on supply chain efficiency [17]. So, demand information sharing is generally the first step for supply chain partnerships. The findings in *Table 5* show that the scenarios having sharing demand information outperform the other ones.

Also, the scenarios having shared costs have higher values in comparison with the ones having production rate sharing. This means that cost sharing has more and better effects on supply chain performance improvement. Knowing the cost values enables the producers to plan their production more precisely and affects the warehouse inventory and system maintenance cost. Therefore, this result is reasonable and acceptable.

Based on the simulation results, we find that production rate information sharing is better than capacity information sharing because the production rate also covers the capacity. The results also show that the no information-sharing scenario (N) is better than some partial information-sharing scenarios. Although this seems most unreasonable, it is an interesting and meaningful result.

According to the simulation, sharing only production rate and/or inventory and/or capacity information, without any demand information sharing, amplifies the bullwhip effect and may mislead the inventory control and production plan and the sales forecast.

Table 5. Cross-efficiency and overall rating for 15 SCM information-sharing scenarios.

Scenario	N	C	D	I	V	P	D&C	D&I	C&I	C&V	D&V	I&V	C&P	D&P	I&P	V&P	F
N	1.000	0.362	0.443	0.509	0.699	0.723	0.258	0.383	0.389	0.679	0.784	0.412	0.552	0.670	0.366	1.000	0.213
C	0.842	0.897	1.000	0.812	0.809	0.899	0.994	0.983	0.923	0.923	0.860	0.752	0.890	0.906	0.677	0.876	1.000
D	0.505	0.611	1.000	0.589	0.900	0.922	0.954	0.766	0.487	1.000	1.000	1.000	0.999	1.000	0.987	1.000	1.000
I	1.000	0.669	0.998	1.000	0.879	0.888	0.733	1.000	0.872	0.751	0.599	0.986	0.680	0.605	0.741	0.864	0.766
V	0.869	0.824	1.000	0.776	1.000	0.981	0.875	1.000	1.000	0.664	1.000	1.000	0.657	0.999	0.990	1.000	1.000

Table 5. Continued.

Scenario	N	C	D	I	V	P	D&C	D&I	C&I	C&V	D&V	I&V	C&P	D&P	I&P	V&P	F
P	0.743	0.431	1.000	0.444	1.000	0.951	0.822	0.898	0.998	1.000	1.000	0.559	1.000	0.325	0.353	1.000	0.967
D&C	0.801	0.918	1.000	1.000	1.000	0.997	0.986	0.972	0.892	1.000	1.000	0.802	0.899	1.000	0.804	0.991	1.000
D&I	1.000	0.653	0.999	1.000	0.991	0.809	0.987	1.000	0.722	0.876	1.000	0.954	0.705	1.000	0.866	0.871	0.831
C&I	0.937	0.933	1.000	0.865	0.659	0.598	0.897	0.958	0.973	0.348	0.764	0.702	0.229	0.691	0.655	0.360	1.000
C&V	0.680	0.823	0.976	0.411	0.444	0.402	0.876	0.644	0.877	0.878	0.890	0.681	0.784	0.800	0.515	0.670	0.912
D&V	1.000	0.967	1.000	1.000	0.779	0.654	1.000	1.000	0.989	1.000	1.000	0.995	0.986	0.799	1.000	1.000	0.876
I&V	0.864	0.779	1.000	0.430	0.800	0.765	1.000	0.739	1.000	0.233	0.854	0.998	0.312	0.691	0.416	0.819	0.603
C&P	0.627	0.544	0.996	0.899	0.633	0.628	0.999	0.450	0.678	0.679	1.000	0.857	0.996	0.971	0.534	1.000	0.875
D&P	0.903	0.809	1.000	0.996	0.702	0.655	1.000	0.879	0.976	0.987	1.000	1.000	1.000	1.000	0.212	1.000	1.000
I&P	0.755	0.990	1.000	0.954	0.899	0.765	0.991	0.434	0.712	0.345	0.223	0.339	0.465	0.244	0.795	0.418	0.569
V&P	0.970	0.540	1.000	0.994	0.998	0.986	1.000	0.986	1.000	0.983	0.404	0.546	0.832	0.560	0.709	0.999	1.000
F	0.117	0.380	1.000	0.227	1.000	1.000	0.980	0.459	0.635	0.999	1.000	0.847	0.361	0.652	0.899	0.994	1.000
Overall rating	0.800	0.698	0.965	0.759	0.835	0.801	0.903	0.797	0.831	0.785	0.845	0.790	0.726	0.760	0.678	0.874	0.859
Ranking	9	16	1	14	6	8	2	10	7	12	5	11	15	13	17	3	4

5 | Conclusion

In this paper, 17 scenarios were defined to explore the effect of different combinations of demand, capacity, inventory, production rate, and cost-per-unit information sharing. Also, the scenarios that share full information and scenarios with a lack of sharing of information were considered. Simulation results showed that the scenarios N, D, I, V, D & I, D & V, D & P, and F were efficient. Moreover, scenarios in which demand information was shared were more efficient than the other scenarios. Scenarios in which cost was shared were more efficient than scenarios in which production rate information was shared and obtained higher value. Simulation results also showed that the production rate information sharing was better than capacity information sharing. It should also be stated that the lack of sharing of information was better than the sharing of incomplete information. Finally, the scenarios were ranked, and the results showed that scenario D and scenario I&P were in first and last place, respectively. Parameters considered in the ranking process were total cost, fulfillment rate, customer service level, order cycle time, and waiting time. This paper can be developed using the following issues:

I. Considering the multi-echelon supply chain.
II. Development of scenarios and other information sharing.
III. Ranking of scenarios using Multiple Attribute Decision-Making (MADM) methods.
IV. Using average methods other than the simple average method in order to obtain the overall rating numbers.

References

[1] Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2004). *Managing the supply chain: the definitive guide for the business professional* (No. 272468). Mcgraw-hill.

[2] Moberg, C. R., Cutler, B. D., Gross, A., & Speh, T. W. (2002). Identifying antecedents of information exchange within supply chains. *International journal of physical distribution and logistics management*, *32*(9), 755–770. DOI:10.1108/09600030210452431

[3] Childerhouse, P., & Towill, D. R. (2003). Simplified material flow holds the key to supply chain integration. *Omega*, *31*(1), 17–27. DOI:10.1016/S0305-0483(02)00062-2

[4] Towill, D. R. (1997). The seamless supply chain-the predator's strategic advantage. *International journal of technology management*, *13*(1), 37–56. DOI:10.1504/IJTM.1997.001649

[5] Cachon, G. P., & Fisher, M. (2000). Supply chain inventory management and the value of shared information. *Management science*, *46*(8), 1032–1048. DOI:10.1287/mnsc.46.8.1032.12029

[6] Jarrell, J. L. (1998). Supply chain economics: supply chain management and competitive advantage. *World trade*, *11*, 58–61.

[7] Zhao, X., Xie, J., & Zhang, W. J. (2002). The impact of information sharing and ordering co-ordination on supply chain performance. *Supply chain management: an international journal*, *7*(1), 24–40.

[8] Lin, F., Huang, S., & Lin, S. (2002). Effects of information sharing on supply chain performance in electronic commerce. *IEEE transactions on engineering management*, *49*(3), 258–268.

[9] Chizzo, S. A. (1998). Supply chain strategies: solutions for the customer-driven enterprise. *Software magazine*, *1*(4), 9-16.

[10] Holmberg, S. (2000). A systems perspective on supply chain measurements. *International journal of physical distribution & logistics management*, *30*(10), 847–868. DOI:10.1108/09600030010351246

[11] Strader, T. J., Lin, F. R., & Shaw, M. J. (2002). The impact of information sharing on order fulfillment in divergent differentiation supply chains. In *Global perspective of information technology management* (pp. 276–296). IGI Global.

[12] Bourland, K. E., Powell, S. G., & Pyke, D. F. (1996). Exploiting timely demand information to reduce inventories. *European journal of operational research*, *92*(2), 239–253. DOI:10.1016/0377-2217(95)00136-0

[13] Ernst, R., & Kamrad, B. (1997). Allocation of warehouse inventory with electronic data interchange and fixed order intervals. *European journal of operational research*, *103*(1), 117–128. DOI:10.1016/S0377-2217(96)00280-9

[14] Lee, H. L., So, K. C., & Tang, C. S. (2000). The value of information sharing in a two-level supply chain. *Management science*, *46*(5), 626–643.

[15] Chen, F., Drezner, Z., Ryan, J. K., & Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times, and information. *Management science*, *46*(3), 436–443. DOI:10.1287/mnsc.46.3.436.12069

[16] Tan, G. W. (1999). *The impact of demand information sharing on supply chain network*. University of Illinois at Urbana-Champaign.

[17] Thonemann, U. W. (2002). Improving supply-chain performance by sharing advance demand information. *European journal of operational research*, *142*(1), 81–107. DOI:10.1016/S0377-2217(01)00281-8

[18] Zhang, C., & Zhang, C. (2007). Design and simulation of demand information sharing in a supply chain. *Simulation modelling practice and theory*, *15*(1), 32–46. DOI:10.1016/j.simpat.2006.09.011

[19] Ryu, S. J., Tsukishima, T., & Onari, H. (2009). A study on evaluation of demand information-sharing methods in supply chain. *International journal of production economics*, *120*(1), 162–175. DOI:10.1016/j.ijpe.2008.07.030

Ekram Nosratian and Taghavi Fard| Com. Alg. Num. Dim. 2(2) (2023) 136-147

[20] Helper, C. M., Davis, L. B., & Wei, W. (2010). Impact of demand correlation and information sharing in a capacity constrained supply chain with multiple-retailers. *Computers and industrial engineering*, *59*(4), 552–560. DOI:10.1016/j.cie.2010.06.014

[21] Cho, D. W., & Lee, Y. H. (2013). The value of information sharing in a supply chain with a seasonal demand process. *Computers and industrial engineering*, *65*(1), 97–108. DOI:10.1016/j.cie.2011.12.004

[22] Lee, H. L., & Whang, S. (2000). Information sharing in a supply chain. *International journal of manufacturing technology and management*, *1*(1), 79–93. DOI:10.1504/IJMTM.2000.001329

[23] Fiala, P. (2005). Information sharing in supply chains. *Omega*, *33*(5), 419–423.

[24] Zhou, H., & Benton, W. C. (2007). Supply chain practice and information sharing. *Journal of operations management*, *25*(6), 1348–1365. DOI:10.1016/j.jom.2007.01.009

[25] Wu, Y. N., & Cheng, T. C. E. (2008). The impact of information sharing in a multiple-echelon supply chain. *International journal of production economics*, *115*(1), 1–11.

[26] Yu, M. M., Ting, S. C., & Chen, M. C. (2010). Evaluating the cross-efficiency of information sharing in supply chains. *Expert systems with applications*, *37*(4), 2891–2897. DOI:10.1016/j.eswa.2009.09.048

[27] Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429–444.

[28] Boussofiane, A., Dyson, R. G., & Thanassoulis, E. (1991). Applied data envelopment analysis. *European journal of operational research*, *52*(1), 1–15. DOI:10.1016/0377-2217(91)90331-O

[29] Charnes, A., Cooper, W., Lewin, A. Y., & Seiford, L. M. (1994). *Data envelopment analysis theory, methodology and applications*. Springer.

[30] Seiford, L. M., & Thrall, R. M. (1990). Recent developments in DEA: the mathematical programming approach to frontier analysis. *Journal of econometrics*, *46*(1–2), 7–38. DOI:10.1016/0304-4076(90)90045-U

[31] Cooper, W. W., Huang, Z., & Li, S. X. (1996). Satisficing DEA models under chance constraints. *Annals of operations research*, *66*, 279–295. DOI:10.1007/BF02187302

[32] Cooper, W. W., Thompson, R. G., & Thrall, R. M. (1996). Introduction: Extensions and new developments in DEA. *Annals of operations research*, *66*, 3–45.

[33] Cook, W. D., & Kress, M. (1990). A data envelopment model for aggregating preference rankings. *Management science*, *36*(11), 1302–1310.

[34] Sexton, T. R., Silkman, R. H., & Hogan, A. J. (1986). Data envelopment analysis: Critique and extensions. *New directions for program evaluation*, *1986*(32), 73–105. DOI:10.1002/ev.1441

[35] Doyle, J., & Green, R. (1994). Efficiency and cross-efficiency in DEA derivations, meanings and uses. *Journal of the operational research society*, *45*(5), 567–578. DOI:10.1057/jors.1994.84