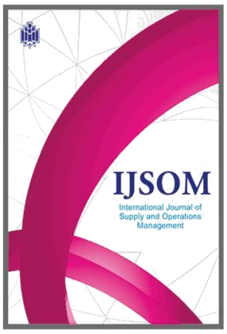
International Journal of Supply and Operations Management

IJSOM

May 2018, Volume 5, Issue 2, pp. 182-191
ISSN-Print: 2383-1359
ISSN-Online: 2383-2525
www.ijsom.com



Performance Evaluation in Green Supply Chain using BSC, DEA and Data Mining

Javad Khalili [a], Alireza Alinezhad [a,*]

[a] *Department of Industrial Engineering, Faculty of Industrial and Mechanical Engineering, Qazvin branch, Islamic Azad University, Qazvin, Iran.*

Abstract
Efficiency is regarded as an important factor for both managers in different companies and organizations and customers who are interested in using the services related to these companies and organizations. However, the biggest challenges managers are coping with include an increase in the competition, an increase in the efficiency of production, and finding suitable suppliers. This study aimed to investigate the efficiency of green supply chain by using Data Envelopment Analysis (DEA) based on Malmquist Productivity Index (MPI) according to the input and output indicators of the Balanced Scorecard (BSC) model and accordingly providing some rules using the decision tree. To this aim, the efficiency of 15 manufacturer firms of automotive parts in Iran was evaluated. Finally, the implicit rules in the data were extracted by using the decision tree. The results indicated that the proposed model had a high degree of accuracy and interpretation in evaluating performance compared to previous models and helps managers to make better decisions.

Keywords: Performance measurement; Green supply chain; Decision tree; MPI; BSC.

1. Introduction

A supply chain takes the form of a network with multiple divisions and relationships. The measurement of supply chain performance which only considers the initial inputs and the last outputs is generally inadequate since it ignores the interactions among the divisions. Thus, an appropriate performance measurement for supply chain should be designed for considering the network characteristics of the chain and interactions. Generally, the larger and more complex the supply chain is, the more challenging it becomes to be measured effectively (Beamon, 1999; Chen & Yan, 2011). In recent years, the performance evaluation in green supply chain management has been very much considered. The basic purposes of green supply chain management performance measurement, or GSCM/PM are: external reporting (economic rent), internal control (managing the business better) and internal analysis (understanding the business better and continuous improvement) (Hervani, Helms, & Sarkis, 2005). Also, market globalization has made supply chain management an interesting topic to be discussed: An efficient supply chain can lead to a range of benefits including reduced cost, increased market share and sales, and sustainable customer relationships (Ferqusen, 2000). Therefore, incorporating green operational strategies in a supply chain should be emphasized by changing the environment.

Charnes, Cooper and Rhodes (1978) pioneered to propose Data Envelopment Analysis (DEA) (Chan & Qi, 2003) as a nonparametric technique for evaluating the relative efficiencies of a set of decision making units (DMUs). DEA is regarded as a powerful mathematical tool for measuring the relative efficiency of a set of DMUs which utilize multiple inputs to produce multiple outputs. Also, DEA is a nonparametric approach that does not require any assumption about the functional

* Corresponding author email address: alinezhad@qiau.ac.ir

form of production (Amini & Alinezhad, 2017). This methodology has been widely used to evaluate the relative performance of a set of production processes, or DMUs, because DEA models need not to recourse to the exact production function regarding multiple inputs and outputs (Charnes, Cooper, & Rhodes, 1978). As the old adage goes: 'you cannot improve what you cannot measure', organizations may need to carry out efficiency measurement for different purposes such as: identifying success, identifying whether they are meeting customer requirements, helping them understand their processes, identifying where problems bottleneck, waste, etc., exist, where improvement is necessary, ensuring that decisions are objective rather than subjective, and showing if improvement planned actually happened (Parker, 2000).

The Balanced Scorecard (BSC) was first identified and implemented by Kaplan and Norton as a performance management tool, following a one-year multi-company study in 1990, which aimed to present management with a summary of the key success factors of a business, and facilitate the alignment of business operations with the overall strategy. (It'…provides a medium to translate the vision into a clear set of objectives, and these objectives are then further, translated into a system of performance measurements that effectively communicate a powerful, forward-looking, strategic focus to the entire organization') (Kaplan & Norton, 1996).

Recently, several studies have been conducted on the evaluating performance of green supply chain based on BSC (Bhattacharya, Mohapatra, Kumar, Dey, Brady, Tiwari, & Nudurupati, 2014; Duarte, 2011; Kim & Rhee, 2012); however, the performance evaluation has been less considered by using DEA model without extracting and examining implicit rules in the data. In addition, the performance measurement of the DMUs may require more than 1 year reaching the output levels given by the input factors.

The present study aimed to evaluate the performance of green supply chain (GSC) by using an integration of BSC, Malmquist productivity index (MPI) and decision tree models. The proposed model was investigated in the form of a case study in automotive parts manufacturing industry, Iran.

The rest of the paper is organized as follows. Section 2, section 3 and section 4 are related literature, methodology, result, and finally, section 5 is the conclusion.

2. Literature Review

There have been some studies conducted on the combination of DEA and BSC. Eilatet, Golany and Shtub (2008), presented a multi-criteria model for evaluating research and development projects by using integrates BSC and DEA and developed an extended DEA model. Amado, Santos and Marques (2011) used the practical relevance of the BSC-DEA model and tested by using it to assess the performance of DMUs in a multinational company which operates in two business areas. Garcia-Valderrama, Mulero-Mendigorri and Revuelta-Bordoy (2009), have proposed a framework for analysis of the relationships between the four perspectives of BSC of Kaplan and Norton based on DEA and a study has been carried out with 90 companies to illustrate a case of this analysis. Asosheh, Nalchigar and Jamporazmey (2010), have proposed a new approach for IT project selection based on BSC-DEA model

Also, Arabzad, Kamali, Naji and Tavakoli (2013), have provided a systematic approach to evaluate performance of laboratory units based on the BSC-DEA model. Further, to introduce a new approach for selection of right indicators based on BSC-DEA model (Danesh Asgari, Haeri, & Jafari, 2018), presented the BSC-DEA model for efficiency measurement in supply chains management (Haghighi, Torabi, & Ghasemi, 2016), presented a system of performance evaluation for companies by integrated DEA and BSC model (Kadarova, Durkacova, Teplicka, & Kadar, 2015), finding a model for DMUs in various stages of BSC by using BSC-DEA model (Kianfar, Ahadzadeh Namin, Alam Tabriz, & Najafi, 2016) and to introduce a new approach for selection of right indicators based on BSC-DEA model (Tan, Zhang, & Khodaverdi, 2017).

Further, several studies have been conducted on the evaluating performance of green supply chain based on BSC. Kim and Rhee (2012), have examined the impact of green supply chain management critical success factors (CSFs) on the BSC performance by the structural equation modeling, using empirical results from 249 enterprise respondents involved in national green supply chain management business in Korea. Bhattacharya, Mohapatra, Kumar, Dey, Brady, Tiwari and Nudurupati (2014) have delineated a green supply chain (GSC) performance measurement framework using an intra-organizational collaborative decision making (CDM) approach and a fuzzy analytic network process based green-balanced scorecard (GrBSc) has been used within the CDM approach to assist in arriving at a consistent, accurate and timely data flow across all cross-functional areas of a business.

The studies on the integrated DEA and data mining method can be applied to present a DEA model combined with bootstrapping to assess performance of one of the data mining Algorithms (Alinezhad, 2016), presented a way to the efficiency evaluation of business projects by using decision tree and DEA (Sohn & Moon, 2014), present a new integrated

DEA and data mining model which is able to find most efficient association rule by solving only one mixed integer linear programming (MILP) for measuring the efficiency of association rules with multiple criteria (Toloo, Sohrabi, & Nalchigar, 2009), the performance of judicial institutions in order to advance the efficiency and quality of judicial verdict by using the DEA and decision trees (Tsai & Tsai, 2010), present a combination of DEA and requisite data mining techniques same as artificial neural network (ANN) and decision tree are employed in order to enhance the power of predicting the DMUs evaluation performance because of their well-known efficiency, and present precise decision rules for improving their efficiency (Rahimi & Behmanesh, 2012), analyze the business performance and technical efficiency of Taiwan’s ICT industry with the MPI of DEA and decision tree (Chiang, Cheng, & Leu, 2017). Wu (2009), have presented a hybrid model using DEA, decision trees and neural networks (NNs) to assess supplier performance. Their results yield a favorable classification and prediction accuracy rate.

3. Methodology

The purpose of present research is to evaluate the performance of GSCM. To this aim, the green indicators of efficiency evaluation in green supply chain were determined by using the BSC. The efficiency of the DMUs was characterized by using the MPI, and according to it inefficient and efficient DMUs were determined. Finally, the implicit rules in the data were extracted by using the decision tree.

3.1. Balanced scorecard (BSC)

Kaplan and Norton (1996) proposed the BSC, as a method for evaluating efficiency based on financial, internal business process, customer, and learning and growth aspects. The BSC plays a role in strategic planning with a link between organizational strategy and enforcement actions in a chain of cause-and-effect relationships. The BSC is not a tool for identifying strategic problems or developing organizational strategies, it also categorizes strategic problems and measures of the realization of goals and practical steps, and it changes the organization's strategy into action and operational expressions. In this way, the strategic planning results are not suspended and are linked in a clear and transparent way. The BSC is a strategic management tool for measuring whether smaller scale activities are aligned with its large scale objectives in terms of strategy (Alinezhad, 2016). The BSC focuses on the strategic of organization and companies and detection of a small number of financial and non-financial data for monitoring. The BSC is used for learning, informing and communicating system and is implemented at different levels of innovative management strains such as risk management, time management, novelty, on-time production, quality management, project management and value management.

Environmental or ecological factors should be emphasized due to the importance of environmental protection in the supply chain. Nowadays, environmental organizations are interested in adhering to the principles of safety and environmental protection. Therefore, the managers' attention to green production results in increasing productivity and revenue, in addition to preserving the environment. Using the BSC is regarded as an appropriate method for evaluating the performance of the green supply chain management. The BSC can help different organizations to evaluate the performance firms by providing performance evaluation indicators which are appropriate for environmental factors.

The aim of this paper is performance evaluation of the green supply chain by using four perspectives of BSC based on DEA. Figure 1 illustrates the green indicators of performance evaluation in GSCM. Figure 1 provides indicators of performance measures currently being used by leading companies to measure and manage sustainability. These measures include both leading and lagging indicators of financial, customer, internal business process, and organizational learning and growth performance.

On the other hand, they are an example of various metrics that companies are using to measure environmental impacts. There may be some discussion over which perspective these measures belong in, or whether a fifth sustainability perspective in the BSC is appropriate. But that is usually determined through a careful analysis of environmental performance.

3.2. Malmquist productivity index (MPI)

Caves, Christensen and Diewert presented the MPI and developed further by Fare, Grosskopf, Lindgren and Roos (1992) relies on distance functions (Fare, Grosskopf, Lindgren and Roos, 1994). The DEA-based MPI approach has been applied to express the productivity change over time. In the non-parametric framework, it is measured as the product of catch-up (or recovery) and frontier-shift (or innovation) terms, both coming from the DEA technologies. In other words, two primary subjects are addressed in computation of MPI growth. MPI method is referred to as a “catching-up” effect or technical efficiency change and a “frontier shift” effect or technological change. The MPI has the components which are used in performance measurement; such as changes in technical efficiency, change in technological change, change in pure technical efficiency, change in scale efficiency as well as change in total factor productivity. The application of DEA-based MPI approach allows to the dynamic performance evaluation of DMUs along the time and the select of this method is based on the fact that region need more than 1 year arriving at the output levels given by the inputs (Carboni & Russu, 2015). The distance was used in order to calculate the indices. It was assumed that all units are efficient in relation to their production time limit, namely, $D^k(x^k, y^k) = 1$. If the number of DMUs is equal to n during t_1 and t_2, the function is defined as (1).

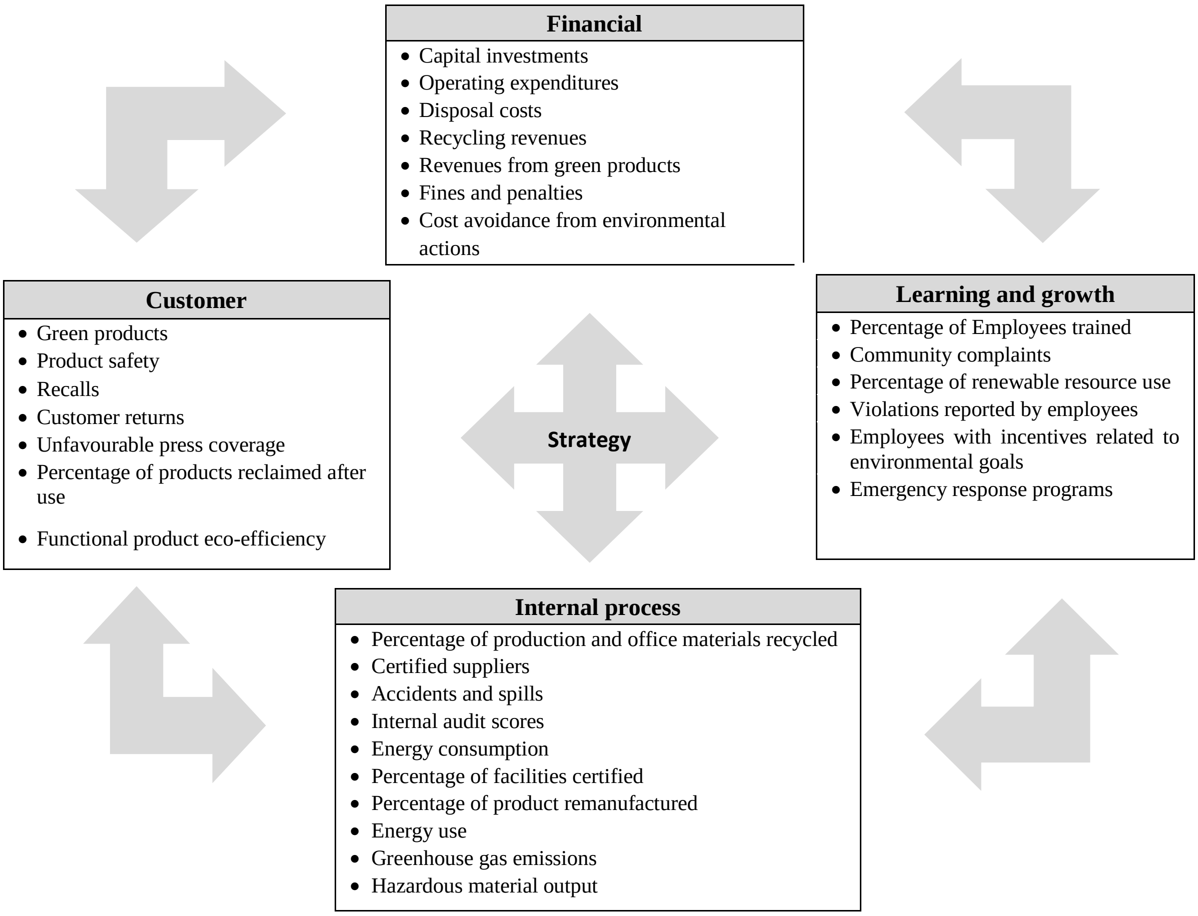


Figure 1. Environmentally based on efficiency evaluation by BSC (Epstein & Wisner, 2001)

$$D^k(x^k, y^k) = min\{\theta | \theta x^{t1}\ produces\ t^2, y^{t1}\} \tag{1}$$

In function (1), $x_j^{t1} = (x_{1j}^{t1}, \dots, x_{mj}^{t1})$ and $y_j^{t1} = (y_{1j}^{t1}, \dots, y_{sj}^{t1})$ respectively the input and output of the unit. The DMU jth at t_1 and $x_j^{t2} = (x_{1j}^{t2}, \dots, x_{mj}^{t2})$ and $y_j^{t2} = (y_{1j}^{t2}, \dots, y_{sj}^{t2})$ respectively, the input and output of the DMU jth at t_2 based on MPI, the productivity growth of the DMU (O) is defined as (2).

$$M_o = \left[\frac{D_o^{t1}(\mathrm{x_o^{t2}, y_o^{t2}})}{D_o^{t1}(\mathrm{x_o^{t1}, y_o^{t1}})} \times \frac{D_o^{t2}(\mathrm{x_o^{t2}, y_o^{t2}})}{D_o^{t2}(\mathrm{x_o^{t1}, y_o^{t1}})}\right]^{\frac{1}{2}} = \frac{D_o^{t2}(\mathrm{x_o^{t2}, y_o^{t2}})}{D_o^{t1}(\mathrm{x_o^{t1}, y_o^{t1}})}\left[\frac{D_o^{t1}(\mathrm{x_o^{t2}, y_o^{t2}})}{D_o^{t2}(\mathrm{x_o^{t2}, y_o^{t2}})} \times \frac{D_o^{t1}(\mathrm{x_o^{t1}, y_o^{t1}})}{D_o^{t2}(\mathrm{x_o^{t1}, y_o^{t1}})}\right]^{\frac{1}{2}} \tag{2}$$

Then:

$$D_o^{t2}(\mathrm{x_o^{t1}, y_o^{t1}}) = \mathrm{Min}\ \theta \tag{3}$$

St:

$\mathrm{x^{t1}}\lambda \ \leq \ \theta\, x_o^{t1}$,

$\mathrm{y^{t1}}\lambda \ \geq \ \mathrm{y_o^{t1}}$,

$\lambda \ \geq 0$.

And:

$$D_o^{t2}(\mathrm{x_o^{t1}, y_o^{t1}}) = \mathrm{Min}\ \theta \tag{4}$$

St:
$x^{t2}\lambda \le \theta x_o^{t1}$,

$y^{t2}\lambda \ge y_o^{t1}$,

$\lambda \ge 0$.

Similarly, $D_o^{t1}(x_o^{t2}, y_o^{t2})$ and $D_o^{t2}(x_o^{t2}, y_o^{t2})$ are calculated. By considering the framework of output-oriented MPI, the interpretations of M_o will be as follows:

- $M_o > 1$: the efficiency has increased;
- $M_o = 1$: the efficiency has constant;
- $M_o < 1$: the efficiency has decreased.

3.3. Decision tree

Data mining is a knowledge which has expanded during the recent years. Data mining is a process of discovering hidden knowledge within the data which is widely used in various fields by describing, predicting and controlling various peripheral phenomena. The decision tree is one of the data mining algorithms and it is the model of decisions and their possible consequences. A decision tree consists of three types of nodes (Kaminski et al., 2018):

- Decision nodes – typically represented by squares;
- Chance nodes – typically represented by circles;
- End nodes – typically represented by triangles.

Also, decision tree is including the root and leaf nodes and branches. The root node is as the starting point. The root node and leaf node are including questions to be answered. Each Branch is arrow connecting nodes, and shows flow from question to answer. The node has two or more nodes extending from it. The decision tree is a flowchart that uses a tree graph of decisions and possible consequences, including chance event outcomes and resource costs. Decision trees are used in operations research and management. The tree methods include chi-squared automatic interaction detection, classification and regression trees C 4. 5 and C 5. 0. In C 4. 5, the target is nominal and inputs may be nominal or interval. A major advantage of the decision tree over other modeling techniques is related to the production of a model which may represent interpretable rules or logic statements. The interpretation capability which exists for trees producing axis parallel decision surfaces is regarded as an important feature.

In this research, the algorithm C 4. 5**,** *known* as *"J 4 8* in Weka", was used. C 4. 5 is an algorithm used to generate a decision tree developed by Ross Quinlan, which can use discrete attributes and noisy data. The algorithm selects the best attribute using the irregularity criterion which is able to use traits with very large amounts, due to the use of Gain Ratio. In addition, pruning is done if there is no error in the educational data, which makes the tree more general and is less dependent on the training set. All the deduction methods of the tree start from the root nodes, which provide all the giveb data and reciprocally divide the information into smaller sets, by doing each aspect ratio test in each group. Therefore, C4.5 is a collection of algorithms not an algorithm.

4. Result

Improving the economic and environmental performance among different countries, especially among automotive manufacturing companies is regarded as an urgent task for all manufacturing companies. This approach can reduce the number of manufacturers which play significant roles in environmental issues in Iran. In addition, the government agencies emphasize the respect of environmental regulations and monitor all manufacturing companies.

Considering the importance of the performance measurement in the green supply chain in automotive industry, the present study implemented the BSC-DEA integrated model to evaluate the performance of 15 automotive parts manufacturer in Iran. As illustrated in Figure 1 and regarding the experts' opinion, the input indicators included the percentage of the employees trained as I_1 (%), the accidents and spills as I_2 (number), and the operating expenditures as I_3 ($). Further, the output indicators included the revenues from green products as O_1 ($), and the green products as O_2 (unit). Table 1 display the input and output values. In the next procedure, the green supply chain efficiency of 15 part manufacturers (DMUs) was evaluated in the automotive parts manufacturing industry in Iran. Table 2 displays the *Malmquist scores* of 15 part manufacturers (DMUs) during 2013-2016 by using DEA-solver. Results show that in DMU_6, DMU_9, DMU_{10}, DMU_{15} efficiencies have decreased (< 1) and DMU_{10} has the lowest performance. In other DMUs efficiencies have increased ($>$ 1). DMU_{14} has the highest performance.

Table 1. The input and output values

DMU	2013					2014				
	(I_1)	**(I_2)**	**(I_3)**	**(O_1)**	**(O_2)**	**(I_1)**	**(I_2)**	**(I_3)**	**(O_1)**	**(O_2)**
DMU 1	75	1	39622	18672	690000	90	2	38500	19652	760000
DMU 2	80	0	14564	6445	364000	100	1	13854	6800	396000
DMU 3	45	0	1211354	819000	920000	60	1	1126365	854000	956000
DMU 4	75	2	69500	34511	610000	50	0	68125	36200	590000
DMU 5	60	1	564412	179402	1850000	70	2	589842	180000	2250000
DMU 6	75	1	16400	7154	100000	55	3	18514	6713	122000
DMU 7	75	2	3694	3065	342000	60	1	3525	2554	385000
DMU 8	85	0	62764	29352	264000	70	1	63324	33452	251000
DMU 9	75	0	892234	400000	775000	100	0	898647	421012	770000
DMU 10	70	1	217125	157954	120000	65	2	225542	145452	110000
DMU 11	80	2	288956	149354	95000	75	1	285621	156120	115000
DMU 12	100	2	25312	18261	211000	70	1	24547	17536	263000
DMU 13	75	0	46845	11965	1350000	55	0	45524	10554	1850000
DMU 14	80	1	4233	1125	141000	70	1	3822	1365	126000
DMU 15	60	2	65694	34635	1110000	80	1	72846	31023	1000000

Table 1. Continued

DMU	2015					2016				
	(I_1)	**(I_2)**	**(I_3)**	**(O_1)**	**(O_2)**	**(I_1)**	**(I_2)**	**(I_3)**	**(O_1)**	**(O_2)**
DMU 1	75	0	39000	17100	778000	80	1	41300	18909	792000
DMU 2	85	0	17566	7260	410000	70	0	14458	7040	396000
DMU 3	60	0	1223420	924630	1106000	40	3	1423641	1054341	1056000
DMU 4	90	1	75524	32452	610000	75	1	73107	35376	660000
DMU 5	80	2	580896	261231	2200000	100	1	614955	250251	2640000
DMU 6	65	1	20535	7352	130000	45	1	20629	7309	132000
DMU 7	65	0	3524	2926	380000	50	2	3830	2672	350000
DMU 8	70	0	58623	31115	245000	60	0	61444	32205	264000
DMU 9	70	1	871604	480770	782000	100	1	852705	501692	792000
DMU 10	95	1	272542	115264	120000	70	2	283927	122323	132000
DMU 11	70	1	295624	147540	121000	80	0	315583	159640	120000
DMU 12	65	2	25186	18512	260000	60	3	26246	20673	264000
DMU 13	45	0	45221	12145	1880000	40	1	46111	13223	1920000
DMU 14	80	0	3860	1470	128000	85	0	3955	1532	132000
DMU 15	70	1	73125	35263	1020000	90	2	75016	35683	1056000

Table 2. Malmquist score *and ranking of DMUs*

DMU	Malmquist score	interpretation
DMU $_1$	1.022	increase
DMU $_2$	1.087	increase
DMU $_3$	1.121	increase
DMU $_4$	1.028	increase
DMU $_5$	1.022	increase
DMU $_6$	0.940	decrease
DMU $_7$	1.080	increase
DMU $_8$	1.055	increase
DMU $_9$	0.906	decrease
DMU $_{10}$	0.855	decrease
DMU $_{11}$	1.158	increase
DMU $_{12}$	1.035	increase
DMU $_{13}$	1.024	increase
DMU $_{14}$	1.442	increase
DMU $_{15}$	0.966	decrease

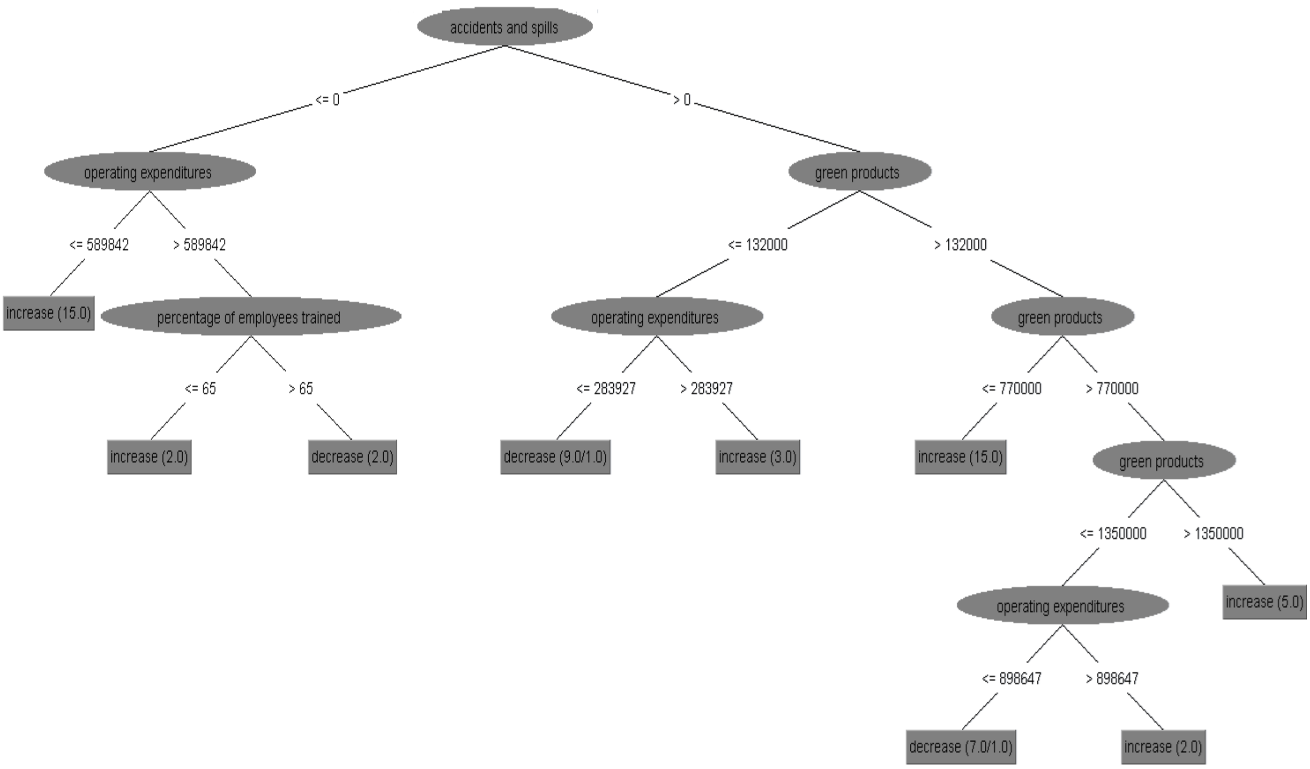


Figure 3. Decision tree derived from the implementation of the model

The features used in the decision tree include the input and output indicators, as well as the efficiency of the DMUs, based on the MPI (classes). In order to confirm the validity of the model, 70% and 30% of the data were selected as the training data set, and the validity of the research, respectively. The data were randomly selected from the Microsoft Excel software. Then, as shown in Figure 2, the decision tree was drawn based on algorithm (j48) by using the Weka software.

As illustrated in Figure 2, the companies were divided into two groups based on the accidents and spills indicator including those having accidents and spills more than zero and those with accidents and spills less than or equal to zero.

The companies with less than or equal to zero accidents and spills were divided into two branches based on the operational expenditure of more than 589842 $ and less than or equal to 589842 $. Based on the results, the companies with less than or equal to zero accidents and spills and operating expenditures of less than or equal to 589842 $ had a higher performance reported to be more than one.

In addition, the companies with the operational expenditures of more than 589842 $ were divided into two branches based on the percentage of the employees trained more than 65% and less or equal 65%. The companies with less than or equal to zero accidents and spills and the operating expenditures of more than 589842 $ as well as the percentage of the trained employees more than 65% had a lower performance reported to be lower than one. Further, the companies with accidents and spills less than or equal to zero and more operational expenditures with the price of 589842 $ and the percentage of the trained employees trained less than or equal to 65% had a higher performance reported to be more than one.

5. Conclusion

Nowadays, enhancing the level of efficiency in production and finding suitable suppliers are the biggest challenges facing managers due to an increasing competition among the companies and manufacturing centers. A supply chain takes the form of a network with multiple divisions and relationships. In recent years, the evaluation of the performance in green supply chain managementhas attracted a lot of attention. Due to the significance of environmental protection in the supply chain, the role of environmental factors or ecological factors should be emphasized. Therefore, the managers' attention to the green production results in increasing the productivity and revenue as well as preserving the environment.

The present research is based on an integrated BSC, MPI approach.. For this purpose, the increased (> 1) and decreased (< 1) efficiency from MPI and the values of the input and output indicators for the MPI were used as the inputs of the decision tree, which are more comprehensive than those used in the previous studies. Recently, several studies have been conducted on evaluating the performance of green supply chain based on BSC (Bhattacharya, Mohapatra, Kumar, Dey, Brady, Tiwari, & Nudurupati, 2014; Duarte, 2011; Kim & Rhee, 2012), however, the performance evaluation was less considered by using DEA model and the implicit rules in the data were not extracted and examined in these studies. In addition, the previous studies were dynamically based and focused more on the time factor. Therefore, the performance of each decision maker evaluates the performance of other DMUs, along with the performance of the same DMUs during last decades.

DEA-based MPI is regarded as a powerful mathematical tool for measuring the efficiency of a set of DMUs along the time (more than 1 year). In order to determine the input and output indicators of the MPI model, one of the best ways is the four perspectives of BSC based on experts' opinion. The BSC helps managers for evaluation of their organizations. According to the main aim of this paper, inputs and outputs are determined based on environmental indicators. This integrated approach makes a powerful technique for performance evaluation. On the other hand, there is a big data in each research. The decision tree is one of the most important tools in extracting implicit rules in a set of data. These rules help managers and experts to make better decisions. Therefore, the present study aimed to evaluate the performance of GSC using an integrated model of BSC, MPI and decision tree. First, the green indicators of performance evaluation in green supply chain were determined by using the BSC. The efficiency of DMUs was characterized by using the DEA- based MPI and accordingly the inefficient and efficient DMUs were determined. Finally, by using the decision tree, the implicit rules were extracted in the related data. Finally, the proposed model was investigated in the form of a case study in Iran automotive parts manufacturing industry. The results indicated that the proposed model had a high degree of accuracy and interpretation in evaluating the performance, compared to the previous models which can help managers to make better decisions in order to increase the efficiency. Further research can be conducted by using the neural network and its comparison with the results of the decision tree.

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