International Journal of Supply and Operations Management

IJSOM

November 2014, Volume 1, Issue 3, pp. 371-391

ISSN-Print: 2383-1359 ISSN-Online: 2383-2525

www.ijsom.com



Analyzing the operations strategies of manufacturing firms using a hybrid Grey DEA approach – A case of Fars Cement Companies in Iran

Mohamad Amin Kaviani a, Mehdi Abbasi *a

^a Department of Industrial Engineering, College of Engineering, Shiraz branch, Islamic Azad University, Shiraz, Iran

Abstract

In competitive markets, the operations strategies of companies are normally formulated based on their competitive advantages. An effective operations strategy should maintain and improve competitive advantages based on the capabilities of the corporate operations resources. Considering the market requirements and the operational performance of the rivals is the key for success and survival of a company in the competition. Therefore, recognizing where a company stands in comparison with its rivals and adopting the appropriate operations strategy plays vital roles in the success of companies. This paper proposes a method for comparing and ranking operations strategies of companies based on the concept of efficient frontier using data envelopment analysis (DEA) in grey environment. In the aforementioned method, DEA is used to evaluate the efficiency of operations strategies of manufacturing firms. Also, grey theory is used to support the uncertainty of the experts' opinions regarding the inputs and outputs of the DEA model. Then the respective units are ranked, and analyses are performed. The proposed approach is applied for the entire nine cement factories of Fars Province in Iran, and the units are ranked, respective analyses are presented regarding the efficient and inefficient units.

Keywords: Operations strategy; Competitive advantages; Performance objectives; Efficient frontier; Prioritizing; Grey DEA.

.

^{*} Corresponding author email address: abbasi_m@iaushiraz.ac.ir

1. Introduction

In the current competitive ambience of industries, managers' strategic decisions are substantial for the organizations in order to lead them toward their long-term goals. Formulating the operations strategies by taking day-to-day experiences into consideration, leads to acquire sustainable competitive advantages. Therefore, managers should provide and improve the competitive advantages by making proper decision in the operations function. This entails a precise operations strategy analysis of the firm in comparison with the rivals and the best practices. Operations strategy is one of the most important factors in the business planning of every organization (Beckman and Rosenfield, 2008). In a systematic market-based perspective, strategic decisions are made according to the business circumstances and market requirements. Operations strategy is the generic pattern of decisions which shape all types of operations capabilities in a long-term period and their contribution to the overall strategy (Slack and Lewis, 2011). To maximize the efficiency of the operations strategies, the managers should seek the continuous improvement of the performance operations and simultaneously move in line with the business strategy of the organization. Furthermore, operations strategy is inseparably linked to the concept of "competitive advantage" (Chambers et al., 2004). Possessing sustainable competitive advantage to survive in every competitive market is totally necessary for efficient enterprises. What is interpreted by the sustainability of competitive advantage is the fact that competitive advantage should comprise different processes from the rivals (the durability is industry-dependent) and be hard to copy, replace or transfer. Competitive advantages, known as "performance objectives," are divided into the five categories of quality, cost, dependability, speed, and flexibility (Slack and Lewis, 2011). Aforementioned performance objectives are used to rank and analyze the operations strategies of the firms.

One of the important concepts in operations strategy literature is the concept of efficient frontier. A company with a position on the efficient frontier, is an operationally efficient unit, moreover, it ranks among the best practices of the industry. If the company fails to position on the efficient frontier, it is not operationally efficient and should strive to reach the best practices and position on the efficient frontier. It is important to point out a number of organizations that are not content with the remaining on the efficient frontier, tend to push out the efficient frontier by redefining market requirements through work on novel delights. (Chambers, 2004; Slack and Lewis, 2011). On the other hand, DEA is a method for analyzing and measuring the relative efficiency of units by having different inputs and outputs (Charnes et al., 1978). Wide applications of DEA in various problems indicate the popularity of this method in measuring efficiency and productivity (Jahanshahloo et al., 2013). Traditional DEA models are CCR and BCC or a combination of these two models. The CCR (Charnes, Cooper and Rhodes) model was first presented by Charnes et al. (1978) for measuring the efficiency of decision making units (DMUs) under constant return to scale assumption. Then the BCC (Banker, Charnes, and Cooper) model was proposed by Banker et al. (1984) by considering variable return to scale assumption. In the BCC model, variable return to scale can be increasing, decreasing or constant. In addition, one of the important subjects in DEA is the concept of "efficient frontier" (Korhonen, 2002). By using optimization techniques, such as linear programming (LP), in which it specifies whether the respective decision-making unit is on or within the efficient frontier, we intend to separate efficient and

inefficient units from each other (Seiford and Thrall, 1990).

The given studies on the circumstances governing the problem are caused to use BCC model in this research. Also, due to existence of ambiguous information in experts' opinions, grey DEA and interval grey numbers are used to support the uncertainty. Grey numbers cover the weakness of the BCC method regarding the uncertainty of input and output data and support the vagueness in the experts' opinions.

One of the goals of this research is to declare the concept of efficient frontier in operations strategies particularly in DEA method. Operations strategy empowers companies to identify their status in comparison with their rivals and make a major contradistinction in terms of utility. This research is applied for Fars Province cement companies in Iran.

It should be noted that there is the assumption of the same products and market targets while the efficiency of the operations strategies are investigated in the whole cement factories. The innovation of this research is to develop a homologous and bilateral relationship between the two concepts of "efficient frontier in operations strategy" and "DEA method and grey DEA." According to the author's investigation, there has been no research in such aspect and by this, we mean adapting DEA model in the operations strategy, consequently this is a completely novel, noteworthy subject.

The rest of the paper is organized as follows: the second and third sections of the paper respectively look into the related studies and methodical foundations of the research, The fourth section roots around the research methodology and it's execution in Fars Province cement companies. The fifth section renders a conclusion and proposals for further researches.

2. Literature Review

As *Gardner* (2004) discusses, an organization can be considered as a system. Operations strategy fundamentals are based on strategic thinking and strategic thinking is totally related to system perspective (*Liedtka*, 1998). System thinking focuses on the system as the whole and the efficiency of the whole system is not optimized unless the efficiency of each subsystem is at optimal point (*Gardner*, 2004). Thus, the operational efficiency, as a component of the whole efficiency of an organization, effects on the overall performance of a firm and measuring the operational efficiency helps the firm to maximize its overall efficiency. Therefore, optimal operational efficiency of an organization can lead getting the high operational performance and finally gaining the efficient operations strategy.

Numerous researches have been performed in the field of utilization of DEA method for evaluating the operational efficiency of manufacturing and service enterprises. *Braglia et al.* (2003) compared the relative efficiency of the steel industrial factories as well as the calculation and rank of efficient units by means of the Anderson-Peterson technique. They also presented managerial solutions for achieving the optimal status of operational strategy of the factories under study. *Talluri et al.* (2003) used competitive advantages as inputs to the DEA model for comparing the efficiency of 51 suppliers categorizing them into three groups using statistical analyses. Employing a special model in DEA called super slack-based model, *Düzakin E. and Düzakin H.* (2007) investigated the operational efficiency of 500 major efficient companies in Turkey. The model which was used in their research was capable of ranking efficient units, therefore they

presented the rankings of the companies under this study. For comparing the operational efficiency of European airports, *Barros and Peypoch* (2009) presented a two-level DEA model. By selecting CCR model at the first level, they ranked airports, and at the second level, they proposed methods for efficiency improvements in the airports that had low operational efficiency using regression analysis and the "benchmark" concept in DEA.

Another research on evaluating operational efficiency was the one by *Meenakumari et al.* (2009) who utilized two of CCR and BCC models for measuring the operational efficiency of 29 electronic public companies. With deliberation of inefficient units, they recommended the use of potentials to improve the efficiency of inefficient units as well as efficient units to achieve the desirable level of efficiency. *Liu et al.* (2010) used DEA to measure the operational efficiency of the thermal power plants of Taiwan. Conducting return to scale of analysis in increasing, decreasing, and constant modes, they stated a series of suggestions for the under-studied units to become more efficient. *Nath et al.* (2010) examined the effects of operational and marketing capabilities of organizations on their performance. In this research, DEA method was used and financial and operational efficiency of the organizations were evaluated through the resource-based view.

In particular *Sun* (2011) was investigated and ranked six among manufacturers in Taiwan's Science and Industry Park having used the DEA method and Malmquist productivity index. With the Combination of DEA and performance matrix, *Memon and Tahir* (2012) who evaluated the operational efficiency of 49 companies in Pakistan, consequently demonstrated that DEA results can be also applied to the performance matrix. Moreover, with the combination of both DEA and life cycle assessment, *Iribarren et al.* (2013) examined 29 wind farms based on their operational performance. *Kaviani et al.* (2014) used the integrated approach of importance-performance matrix and fuzzy AHP to prioritize the operations strategies of a number of cement companies in Fars Province. They set as comparison criteria the five competitive advantages of quality, cost, flexibility, delivery speed, and dependability. Selecting four competitive advantages as inputs to the DEA model and two indices as model outputs, *Bulak and Turkyilmaz* (2014) evaluated the efficiency of 744 production units from 10 sections of industry.

On the other hand, the applications of Grey DEA in efficiency measurement have been increased significantly in recent years. For instance, by using the DEA model and grey relational analysis, *Wang et al.* (2007) measured the efficiency of hospitals in China and the observed indicators were reduced from 9 to 5. Wang *et al.* (2009) used a super efficiency grey DEA model to evaluate the energy efficiency in China. The information from the period of 1995 and 2005 was used in the aforesaid research.

The other examples are *Shuai and Wu* (2011) who used the DEA method and grey entropy to evaluate the impact of internet marketing on the performance of Taiwan's hotels. They demonstrated the fact that operational efficiency and internet marketing have a direct relationship with marketing efficiency effects. And *Chen Y. and Chen B.* (2011) who also exploited a combination of grey DEA and Malmquist productivity index for evaluating the operational performance of wafer fabrication industries in Taiwan. They examined efficiencies in the two modes of efficiency in constant and variable return to scale, and consequently compared the results. Lastly *Le et al.* (2014) used grey DEA for measuring the efficiency of the Vietnamese garment industry.

The authors' investigations corroborate that no study has been executed in analyzing and ranking the operations strategy of manufacturing firms using the grey DEA approach. The current research sought to fill this gap.

3. Theoretical Principles of the research

3.1. Operations Strategy

The responsibility of operations as a functional unit in organizations is to transform operations resources into products and services (*Brown et al. 2013*). A review of the literature on operations strategy shows that from the outset, the activity of the functional field of operations has not been of interest as a factor that creates competitive advantage. The competitiveness of the work environment drew greater attention to the decisions pertaining to operations. *Skinner*'s 1969 paper titled "Manufacturing-missing link in corporate strategy" was a preamble to the introduction of manufacturing and operations into the strategic decisions of companies.

Over the years, the concept of operations strategy has been defined in different ways: operations strategy is an integrated pattern of decision making in operations that is linked to business strategy (Hayes and Wheelwright, 1984); operations strategy is a general pattern for decisions that shape the long-term capabilities of any kind of operations and the way they contribute to the overall strategy through ongoing reconciliation of market requirements with operations resources (Slack and Lewis, 2011). On the one hand, operations strategy meets the requirements determined by business strategy and, on the other hand, it aids the organization by incorporating customer requirements into operations capabilities which leads to introducing the company to new markets and developing new opportunities for it (Beckman and Rosenfield, 2008). Paying attention to these definitions demonstrates what they have in common is that operations strategy could be developed through creating competitive advantage. In fact, the main role of operations strategy is to convert the competitive advantages of organization to operations capabilities (Boyer and Lewis, 2002). According to the definition by Slack and Lewis (2011), operations strategy reconciles operations resources to market requirements. This indicates two important viewpoints consist of the market-based view (external) and the resource-based view (internal) in formulating operations strategy of organizations.

3.1.1. Concept of efficient frontier in operations strategy

According to authors' knowledge, the concept of operations strategy efficient frontier was first introduced by *Slack et al.* (2006). Figure 1 shows the concept of efficient frontier in operations strategy, and the relative performance of a number of organizations in the same industry may be seen in it. Organizations A, B, C, and D are located on the efficient frontier curve. In the short term time horizon, it is impossible for the organization to simultaneously achieve excellent performance in all aspects of competitive advantages. Whereas, in the long term, the improvement of the entire competitive advantages (performance objectives) is the goal of operations strategy. The explanations are provided in this section are based on the two competitive advantages, variety and cost efficiency.

The organizations that are located on the efficient frontier of their industry are on different

positions on the frontier compared to each other due to different marketing strategies and managerial viewpoints. Organization X is inefficient in terms of operations due to failing to create a trade-off between the two competitive advantages. Organizations B and X are on the same line. However, because of better trade-off between the two performance objectives, Organization B is placed on the efficient frontier like the best rivals, while Organization X is not on the efficient frontier. The companies on the efficient frontier (the best practices in the industry) can improve their operational efficiency by overcoming implicit trade-off on the efficient frontier curve. Organizations not located on the efficient frontier should benchmark best practices of the industry by redefining their operations strategy and following the organizations situated on the efficient frontier (*Slack and Lewis*, 2008, 2011; *Slack et al.*, 2006).

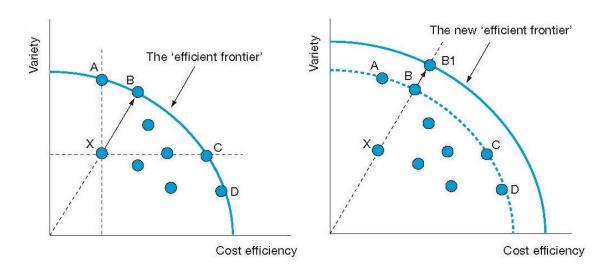


Figure 1. Concept of efficient frontier in operations strategy (Slack et al. 2006)

3.1.2. Competitive advantages and performance objectives

Competitive advantages are factors that enable an organization to compete and survive in a competitive market (*Slack and Lewis*, 2008). Given the strategic role of operations, competitive advantages are associated with organization performance (*Slack and Lewis*, 2011). Introducing competitive advantages as "performance objectives," competitive priorities link the operations strategy of organizations with their performance. On the other hand, competitive advantages are considered the achievable goals of the manufacturing section of the organizations. In the literature of operations management, competitive advantage emphasizes on the strategic importance of operations resulting in the achievement of sustainable competitive advantage. Supporting business strategies in manufacturing firms are among other goals of competitive advantages (*Bulak and Turkyilmaz*, 2014).

Slack and Lewis (2011) categorized performance objectives in the five groups of quality, cost, speed, dependability, and flexibility. These five performance objectives illustrate competitive advantages. The definitions of each of the five mentioned competitive advantages are as follows:

- Quality: Performing tasks properly, procuring goods and services without error and in accordance with the previously-determined goals
- Speed: Performing tasks rapidly, minimizing the time between the customers' request for goods or services and the delivery
- Dependability: Carrying out the work in a timely manner, abiding by the delivery commitments promised to the customers
- Flexibility: Changing what you do or the way the work is done, the ability to change or match the activities of operations in order to overcome unexpected circumstances or gain customers' unique behavior or introducing new products or services
- -Cost: Carrying out the work in an inexpensive manner, producing goods and rendering services with a cost that enables them to properly perform pricing for the market in a way that the organization revenue is also allowed for.

3.1.3. Hayes & Wheelwright Four stage model for demonstrating the strategic role of operations

Hayes and Wheelwright (1985) introduced a four-stage model for operations strategies of organizations where the operations capabilities of organizations was displayed from an internal view and the strategic evaluation of rivals was put on display from an external view. They demonstrated that operations strategy should create a vision in which the role of operations resources in business is shown.

The first stage of their model is the internal indifference stage pertaining to organizations that wish to merely solve their problems and are internally neutral. At this stage, the organization has a reactive approach, and operations strategy is not known as a competitive advantage.

The second stage is external indifference comprising organizations that wish to keep abreast with the rivals performing as good as their competitors. These organizations are externally neutral and make use of the "benchmarking" strategy. Since organizations attempt to adopt best practices of the industry at this stage, they cannot outperform them and will equal them at best. This stage is a start to the creation of competitive advantage. However, in this stage, operation is not related to business strategy.

The third stage is internally supportive pertaining to organizations that wish to be the best in their own industry. In the efficient frontier model of operations strategy, these organizations are placed on the efficient frontier and use the "supportive" strategy. At this stage, operations strategy is in line with business strategy and supports it.

The fourth and the best stage is externally supportive pertaining to organizations that create needs in the industry and pioneer in innovation and the creation of requirements and motivation in the market. In the efficient frontier model of operations strategy, these organizations can push out the efficient frontier. At this stage, organizations may perform superior compared to the best practices of the industry.

In the present research, it is assumed, that none of the companies under study are at the first stage of Hayes and Wheelwright's model.

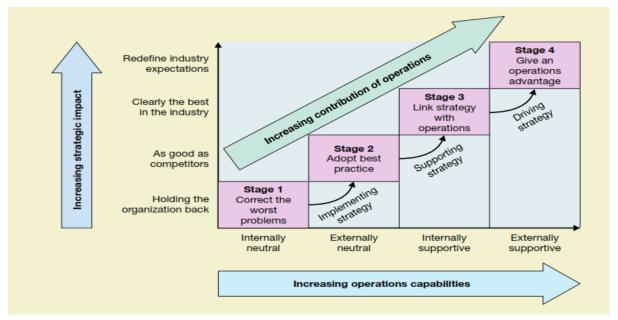


Figure 2. Hayes & Wheelwright Four stage model (Hayes & Wheelwright, 1985)

3.2. Incorporating Grey theory in DEA model

3.2.1. DEA - BCC models

DEA is a powerful method for calculating the efficiency of decision-making units. The return to scale structure is among the features of the DEA model. Return to scale may be constant or variable (*Aji and Hariga*, 2013). The CCR model is among constant return to scale models. In many organizations, a small decision-making unit cannot be compared with a larger decision-making unit by multiplying its inputs and outputs by a constant factor. Hence, in such organizations, constant return to scale does not hold. To resolve this defect, *Banker et al.* (1984) invented a new model by making changes to the CCR model which is known as BCC given the initials of their surnames. As mentioned earlier, the BCC model is used in light of the conditions governing the problem.

3.2.2. Grey systems theory and grey interval numbers

The grey systems theory, which is very similar to Zadeh's fuzzy theory, was presented by *Deng* (1982). Fuzzy mathematics deal with problems where the experts' uncertainty is expressed by membership functions (*Zareinejad et al.*, 2014). If the information and data is inadequate, or there are limitations to the sample volume and the membership function cannot be extracted, the grey systems theory may be applicable. This theory is employed for solving vague problems and those having uncertain data. Using a relatively small volume of information and great variability in criteria, this theory yields satisfactory, desirable outputs. Grey theory, just like fuzzy theory, is an effective mathematical programming model for solving unclear, vague problems (*Deng*, 1982). Greyness in the grey region denotes incomplete information as well as uncertainty.

Each grey system is described by grey numbers, equations, and matrices where grey numbers are

the cells of the system. A grey number may be defined as a number with uncertain information (*Wang et al.*, 2009). For instance, the rank of criteria in a decision making is expressed as a linguistic variable that can be expressed using number intervals. These number intervals include uncertain data. It may also be stated that a grey number is a number which its precise value is unknown, but the interval of its value is known. On the whole, a grey number is expressed by an interval or a set of numbers. Assume that grey numbers exist as follows (*Rahimnia et al.*, 2011; *Alparslan Gok et al.*, 2014):

$$\bigotimes_{1} \in [a, b], a < b$$

 $\bigotimes_{2} \in [c, d], c < d$

In this case, addition, subtraction, multiplication, and division of two grey numbers \otimes_1 and \otimes_2 as well as the inverse of each grey number are defined as follows:

$$\begin{split} & \otimes_1 + \otimes_2 \in [a+b,c+d] \\ & - \otimes = [-b,-a] \\ & \otimes_1 - \otimes_2 = \otimes_1 + (-\otimes_2) \in [a-d,b-c] \\ & \otimes^{-1} \in \left[\frac{1}{b},\frac{1}{a}\right],ab > 0 \\ & \otimes_1 . \otimes_2 \in \left[\min\{ac,ad,bc,bd\},\max\{ac,ad,bc,bd\}\right] \\ & \frac{\otimes_1}{\otimes_2} = \otimes_1 . \otimes_2^{-1} \\ & \frac{\otimes_1}{\otimes_2} \in \left[\min\left\{\frac{a}{c},\frac{a}{d},\frac{b}{c},\frac{b}{d}\right\},\max\left\{\frac{a}{c},\frac{a}{d},\frac{b}{c},\frac{b}{d}\right\}\right],cd > 0 \\ & k. \otimes \in [ka,kb],k \in R^+ \end{split}$$

As noted earlier, given incomplete, ambiguous information in the experts' opinions, interval grey numbers are used in the present research.

3.2.3. Grey DEA model

DEA is a method for measuring efficiency that is capable of determining the relative efficiency of the homogeneous set of decision-making units by having different inputs and outputs (*Talluri et al.*, 2003). For many DEA models, such as BCC, the data are clear and certain. However, in real problems, uncertainty may exist. Since the BCC model works with certain data and cannot be executed for problems involving uncertainty, new changes have been recently made to the DEA method enabling this method to solve problems that involve uncertainty. In general, uncertainty in the real world may be divided into the three types of stochastic, fuzzy, and grey (*Yang*, 1998). Following the introduction of grey systems and logic in 1982 and the DEA model in 1978, *Yang* (1998) introduced the hybrid Grey DEA model using grey interval numbers. He introduced the grey CCR model by presenting upper and lower bound for the model's interval efficiency. Afterwards, various researchers have utilized Grey DEA in their works. *Wang and Liu* (2012) presented a Grey CCR model under the data consistency condition. Their model calculates certain limits in order to compute the upper and lower bound of interval efficiency. In their most recent research based on grey Linear programming, *Xia et al.* (2014) put forward a method for DEA with

grey numbers. Using interval and conventional grey numbers, *Xu and Zhou* (2013) presented Grey DEA for CCR and BCC. In their proposed Grey DEA model, DMUs were categorized in strongly efficient, weakly efficient and inefficient.

4. Research Methodology

The operational efficiency of Fars Province cement companies was investigated from the perspective of their operations strategy. Given research objectives, the stages of conducting the research were as follows:

4.1. Step 1- Identifying DMUs and Determining Inputs and Outputs

The DMUs of this research were the entire cement companies of Fars Province comprising nine factories named as DMU1 to DMU9 to preserve information and for the sake of confidentiality. The information required for DEA inputs and outputs were gathered by direct interviews and examining companies' documentation through visiting the cement factories of Fars Province. To determine inputs and outputs, the criteria were clarified by investigating relevant literature:

With regard to selecting DEA inputs, *Talluri et al.* (2003) considered five competitive advantages, namely quality, cost, time, flexibility, and innovation to be the inputs to the DEA model. *Bulak and Turkyilmaz* (2014) considered four competitive advantages, namely quality, delivery, cost and flexibility to be the inputs to the DEA model. *Sarmiento et al.* (2007) also stated that competitive advantages may be utilized as DEA inputs or outputs to estimate operational efficiency of organizations. The five groups of competitive advantages or, in other words, the performance objectives of *Slack and Lewis* (2008), namely quality, cost, flexibility, delivery and dependability, were used as inputs to the DEA model.

With respect to outputs, it should be noted that efficiency could be measured by using financial and non-financial indices (*Bulak and Turkyilmaz*, 2014). The most typical variables for financial performance are return on investment (ROI) and return on assets (ROA) employed by *Talluri et al.* (2003) as DEA model outputs using a 7-point Likert scale for measuring them. Return on equity, return on sale, and net profit are among other financial indices. Market share was one of the variables used for the non-financial performance. *Bulak and Turkyilmaz* (2014) used the market share index as well as net profit margin as the DEA model outputs using a 5-point Likert scale for measuring output indices. Growth of sale and employees, customer satisfaction, and brand prestige were among other non-financial indices (*Bulak and Turkyilmaz*, 2014).

Two financial variables and one non-financial evaluative variable were used in order to account for both financial and non-financial perspectives for increasing model validity. ROI and ROA are the financial variables and market share (which is provided from yearly net sale) is the non-financial variable as outputs for the Grey DEA model. Table 1 demonstrates input and output variables.

Table 1. Input and Output Variables

Outputs	Variable	Inputs	Variable
ROA	y 1	Quality	\mathbf{x}_1
ROI	y ₂	Cost	\mathbf{x}_2
Market share	Y_3	Dependability	X ₃
	-	Flexibility	X4
Input and Output	Factors	Speed	X5

4.2. Step 2- Data collection for Inputs and Outputs

At this stage, to extract input data for DEA, linguistic variables were used as survey criteria by conducting interviews with the members of the board of directors and the production managers of each of the 9 cement factories of Fars Province and asking for their opinions about the 5 performance objectives pertaining to the factories' operations strategy. It is considerable that interviewed experts of studied companies preferred to explain their opinions for the situation of inputs and outputs as poll criteria. These variables were converted into interval grey numbers. It is noteworthy that it was presumed that people agree about the posed questions. The used scale is shown in Table 2.

Table 2. Scale for Inputs (*Li et al.*, 2007)

Very Low (VL)	Low (L)	Medium Low (ML)	Moderate (M)	Medium High (MH)	High (H)	Vey high (VH)	Scale
[0,0.1]	[0.1,0.3]	[0.3,0.4]	[0.4,0.5]	[0.5,0.6]	[0.6,0.9]	[0.9,1]	Grey interval Number

The data pertaining to the inputs may be seen in Table 3.

Table 3. Interval Grey numbers for Inputs

DMU Number	Quality (X1)	Cost (X2)	Dependability (X3)	Flexibility (X4)	Speed (X5)
1	[0.9,1]	[0.6,0.9]	[0.5,0.6]	[0.9,1]	[0.3,0.4]
2	[0.6,0.9]	[0.9,1]	[0.6,0.9]	[0.5,0.6]	[0.6,0.9]
3	[0.5,0.6]	[0.6,0.9]	[0.1,0.3]	[0.3,0.4]	[0.5,0.6]
4	[0.9,1]	[0.3,0.4]	[0.6,0.9]	[0.9,1]	[0.5,0.6]
5	[0.5,0.6]	[0.4,0.5]	[0.9,1]	[0.5,0.6]	[0.1,0.3]
6	[0.6,0.9]	[0.4,0.5]	[0.3,0.4]	[0.6,0.9]	[0.6,0.9]
7	[0.5,0.6]	[0.9,1]	[0.5,0.6]	[0.5,0.6]	[0.1,0.3]
8	[0.6,0.9]	[0.4,0.5]	[0.6,0.9]	[0.4,0.5]	[0.9,1]
9	[0.6,0.9]	[0.3,0.4]	[0.6,0.9]	[0.4,0.5]	[0.5,0.6]

To gather the values of output variables, a seven-point Likert-type scale was employed instead of a five-point one, where 1 shows the least value, i.e. the poorest performance, and 7 signifies the highest value, i.e. the best performance (*Talluri et al.*, 2003). The seven-point scale was used to create accordance between the used scale and interval grey numbers. In order for the values of input and output variables of the model to match and to convert real numbers to grey interval numbers in the outputs, the following scale is used: (Table 4)

Table 4. Scale for Outputs

Very weak (VW)	weak (W)	Medium Weak (MW)	Moderate (M)	Medium High (MD)	High (H)	Vey high (VH)	Scale
[0,0.1]	[0.1,0.3]	[0.3,0.4]	[0.4,0.5]	[0.5,0.6]	[0.6,0.9]	[0.9,1]	Grey interval Number
1	2	3	4	5	6	7	7-point Likert-type scale

In fact, the value of each output was obtained from the mean value of the past 3 years of each of the nine cement factories. The mean performance of each of the DMUs with regard to the indices is considered in the time interval under study for determining the values of output variables, i.e. the three-year interval from 2011 to 2013. These values were extracted from financial, production,

sale and marketing documents and information as well as other relevant information as presented in Table 5 and Table 6.

Table 5. Real numbers of Outputs based on 7-point scale

DMU	ROA	ROI	Market Share
Number	(Y1)	(Y2)	(Y3)
	(between 1 and 7)	(between 1 and 7)	(between 1 and 7)
1	5	4	5
2	6	3	4
3	4	5	4
4	6	5	5
5	4	3	3
6	5	4	4
7	3	4	5
8	2	3	5
9	4	4	3

Table 6. Interval Grey numbers of Outputs

DMU Number	ROA (Y1)	ROI (Y2)	Market Share (Y3)
1	[0.5,0.6]	[0.4,0.5]	[0.5,0.6]
2	[0.6,0.6]	[0.3,0.4]	[0.4,0.5]
3	[0.4,0.5]	[0.5,0.6]	[0.4,0.5]
4	[0.6,0.9]	[0.5,0.6]	[0.5,0.6]
5	[0.4,0.5]	[0.3,0.4]	[0.3,0.4]
6	[0.5,0.6]	[0.4,0.5]	[0.4,0.5]
7	[0.3,0.4]	[0.4,0.5]	[0.5,0.6]
8	[0.1,0.3]	[0.3,0.4]	[0.5,0.6]
9	[0.4,0.5]	[0.4,0.5]	[0.3,0.4]

4.3. Step 3- Determining the appropriate DEA model depending on the conditions governing the problem

With respect to selecting an appropriate DEA model, input-oriented BCC model was used in this study. The reason lies in the fact that utilizing constant return to scale, and consequently the CCR model, fits a situation where all DMUs work in an optimal scale (*Coelli et al.*, 2005). However, given the competitive circumstances and environmental limitations for the cement companies of Fars Province, the units under study did not work in an optimal scale, and thus, employing variable return to scale is closer to reality. On the other hand, selecting the DEA models as

input-oriented or output-oriented was carried out in light of limitations in increasing input or output resources (*Cook et al.*, 2014). After conducting interviews with factory managers and analyzing the current status of the organizations, as well as that of the competitive market, the input-oriented model was used given the limitation of units in increasing the output variables. Figure 3 demonstrates the DEA model of the problem.

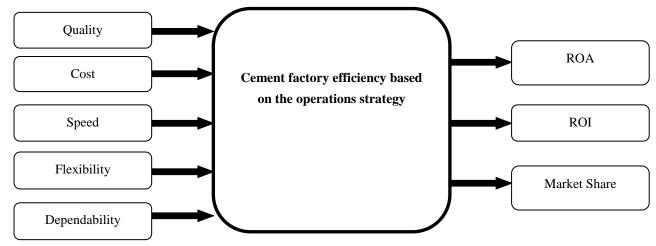


Figure 3. DEA model for the problem

4.4. Step 4 - Creating Grey DEA model

Once the input and output variables and the proper DEA model were determined, the Grey DEA model should be constructed for solving the problem. To do so, the dual model of Grey BCC was used as follows (*Xu and Zhou*, 2013):

$$\begin{split} E_j &= \mathit{Min}\theta \\ & \sum_{j=1}^n (Y_{kj}(\otimes)\lambda_j) \geq Y_{k\circ}(\otimes) \\ j &= 1 \end{split}$$
 St:
$$\sum_{j=1}^n (X_{ij}(\otimes)\lambda_j) \leq \theta X_{i\circ}(\otimes) \\ & \sum_{j=1}^n \lambda_j = 1 \\ & j = 1 \end{split}$$

$$i = 1,2,...,p \,, \, k = 1,2,...,q \qquad \lambda_j \geq 0 \end{split}$$

The above model is a type of grey LP. It was assumed that the grey numbers used in this model were all of the interval type; that is, their minimum and maximum values are known, but their exact value is unknown. $\bigotimes X_{ij} \in [X_{ij}^L, X_{ij}^U]$ and $\bigotimes Y_{kj} \in [Y_{kj}^L, Y_{kj}^U]$ denote interval grey

numbers. U and L indicate upper and lower bounds. Using the characteristics of interval grey numbers, the above-mentioned grey numbers may be written as follows:

$$\begin{split} \boldsymbol{X}_{ij} &= \boldsymbol{X}_{ij}^{L} + (\boldsymbol{X}_{ij}^{U} - \boldsymbol{X}_{ij}^{L}) \boldsymbol{S}_{ij} \\ \boldsymbol{Y}_{kj} &= \boldsymbol{Y}_{kj}^{L} + (\boldsymbol{Y}_{kj}^{U} - \boldsymbol{Y}_{kj}^{L}) \boldsymbol{T}_{kj} \\ \text{Where } \boldsymbol{O} \leq \boldsymbol{S}_{ij}, \boldsymbol{T}_{kj} \leq 1 \end{split}$$

Finally, by converting grey programming to the LP model, interval efficiency was obtained where DMU jo is shown as $E_{j\circ}\in[E_{j\circ}^L,E_{j\circ}^U]$ where the upper and lower bounds of efficiency are achieved by solving the following LP models: (*Wang and Liu*, 2012)

$$E_{j\circ}^{U} = \operatorname{Min}\theta$$
 St:
$$E_{j\circ}^{L} = \operatorname{Min}\theta$$
 St:
$$\sum_{j=1}^{n} (\lambda_{j} Y_{kj}^{L} + \lambda_{j\circ} Y_{kj}^{U}) \geq Y_{kj\circ}^{U}$$

$$\sum_{j=1}^{n} (\lambda_{j} Y_{kj}^{U} + \lambda_{j\circ} Y_{kj}^{L}) \geq Y_{kj\circ}^{L}$$

$$\sum_{j=1}^{n} (\lambda_{j} X_{ij}^{U} + \lambda_{j\circ} X_{ij\circ}^{L}) \leq \theta X_{ij\circ}^{L}$$

$$\sum_{j=1}^{n} (\lambda_{j} X_{ij}^{U} + \lambda_{j\circ} X_{ij\circ}^{U}) \leq \theta X_{ij\circ}^{U}$$

$$\sum_{j=1}^{n} (\lambda_{j} X_{ij}^{L} + \lambda_{j\circ} X_{ij\circ}^{U}) \leq \theta X_{ij\circ}^{U}$$

$$\sum_{j=1}^{n} (\lambda_{j} X_{ij}^{L} + \lambda_{j\circ} X_{ij\circ}^{U}) \leq \theta X_{ij\circ}^{U}$$

$$\sum_{j=1}^{n} \lambda_{j} = 1$$

$$\sum_{j=1}^{n} \lambda_{j} = 1$$

$$\lambda_{j} \geq 0$$
 i= 1,2,...,p,

DMU jo is called strongly efficient, whenever its upper and lower bounds are equal to one, while all slack variable values are zero. Moreover, if the slack variables pertaining to DMU jo have a non-zero value, while the upper and lower bounds of efficiency are equal to one, that DMU is weakly efficient. If upper and lower bounds take values less than one, the respective DMU is inefficient.

4.5. Step 5 – Solving Grey DEA model and ranking DMUs

The relative efficiency of the decision-making units was calculated by solving the Grey DEA model of the research in view of step 3. Table 7 shows the results of solving the DEA models of the decision-making units. The interval efficiencies of the decision-making units indicate the relative efficiency of each DMU. The DMUs were ranked based on a concept called the grey number's "kernel." Liu et al. (2010) explain that if a grey number's kernel is greater than another grey number's kernel, the grey number itself is also greater than the other grey number. The kernel of each grey number is demonstrated by the sign $E(\otimes)$ and is defined as follows: (Liu et al.,

2010)

$$\otimes X_j \in [X_j^L, X_j^U] \rightarrow E(\otimes) = \frac{(X_j^L + X_j^U)}{2}$$

 $E^{\overline{U}}$ E^{L} Kernel Rank $j \circ$ 0.96 DMU1 0.98 2 4 DMU2 0.84 0.88 0.86 DMU3 0.76 0.84 0.80 6 DMU4 1 1 1 1 DMU5 0.77 0.81 5 0.85 DMU₆ 9 0.66 0.72 0.69 0.99 DMU7 0.95 0.97 3 DMU8 0.75 0.710.73 8 DMU9 0.72 0.78 0.75

Table 7. DMUs Interval efficiency

4.6. Step 6 – Analyzing the results

After solving the model, it may be observed in Table 7 that only DMU4 is efficient and is located on the efficient frontier of the DEA model. This indicates that this factory has brought about proper tade-off between the 5 performance objectives achieving optimal efficiency given the financial and non-financial indices of the problem. This efficient DMU is at the third stage of the *Hayes and Wheelwright*'s four-stage model (1985) and may be considered as the best practice in the cement industry. Given the accordance between the concepts of efficient frontier in DEA literature as well as operations strategy literature, it may be interpreted that DMU4, which is recognized as efficient by the DEA model and is positioned on the BCC efficient frontier, is also located on the efficient frontier of the cement industry. It has adopted an appropriate operations strategy with respect to the current market requirements of Fars Province cement industry, thus achieving desirable efficiency in comparison with other rivals.

In addition, cement factories 1 and 7 closely follow the efficient factory 4 with efficiency values near 1. This suggests a competitive atmosphere among these three factories. Given the inefficiency of other DMUs, which are at the second stage of *Hayes and Wheelwright*'s four-stage model, they should move toward efficient frontier. By adopting DMU4 as the benchmark, they should prepare to attain maximum efficiency in the industry and aim at improvement by revising their operations strategies and creating a balance between the performance objectives, so that they would enter the third stage of the aforementioned model. Cement factory 4 is recognized as efficient being located on the efficient frontier of operations strategy of Fars Province cement industry. In circumstances where more than one factory is recognized as efficient unit given the proposed approach, the ranking of the efficient units is required. It is advisable to use super efficiency DEA models in the grey environment.

5. Conclusion and future research

Not only this proposed Grey DEA method evaluated the efficiency of Fars Province cement factories, but also it analyzed the operations strategy of the factories by selecting competitive advantages as input variables in the DEA model. This DEA model in the grey environment seeks to improve operations strategy on the basis of analyzing the efficiency of factories. The accordance between the efficient frontier concept in operations strategy and DEA resulted in the introduction of a new outlook on operational efficiency and its relation with organizations' operations strategy.

In operations strategy literature, resource-based view and market-based view are two important concepts. Operations strategies in the optimal scale should create a balance between these two views. In this study the status of factories was investigated via the market-based view. Inefficient factories' managers should investigate their factories through the resource-based view while their positions were determined in comparison to other rivals. They should change their operations strategies and set efficient factories, as benchmarks, should move toward efficient frontier in order to be able to enhance their and efficiency. This research is applicable for all manufacturing organizations and can be useful for various industries' managers.

Four systems scientic methodologies for uncertain information in problems are Grey system theory, fuzzy theory, rough set theory and probability theory (*Li and Lin*, 2014). Grey and fuzzy theories are more appropriate for combination with DEA in order to analyze the operations strategies of firms. The Grey system Theory was utilized in this paper and fuzzy DEA approach can be used in future studies. Thus, utilizing other multi-criteria decision making techniques in certain and uncertain environments can be useful in order to expand the model, too. Furthermore, it is proposed to investigate the circumstances that a company seeks to achieve the fourth stage of the *Hayes and Wheelwright*'s four-stage model (1985). Conducting similar research in other manufacturing industries can also remarkably assist the managers to improve their operational efficiency.

6. Acknowledgment

The authors would like to thank the editor and the referees for the valuable and constructive comments that have led to a significant improvement in the original paper. This paper is an excerpt from a Master's thesis in Industrial Engineering written and arranged by Mr. Mohammad Amin Kaviani and supervised by Dr. Mehdi Abbasi. The work was supported in part by Islamic Azad University, Shiraz, Iran.

References

Aji, Y., & Hariga, M. (2013). An AHP-DEA-based vendor selection approach for an online trading platform. *International Journal of Applied Decision Sciences*, 6(1), 66-82.

Alparslan Gok, S. Z., Palanci, O., & Olgun, M. O. (2014). Alternative Axiomatic Characterizations of the Grey Shapley Value. *International Journal of Supply and Operations*

Management, 1(1), 69-80.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, 30(9), 1078-1092.

Barros, C. P., & Peypoch, N. (2009). An evaluation of European airlines' operational performance. *International Journal of Production Economics*, 122(2), 525-533.

Beckman, S. L., & Rosenfield, D. B. (2008). *Operations strategy: competing in the 21st century*. McGraw-Hill/Irwin.

Boyer, K. K., & Lewis, M. W. (2002). Competitive priorities: Investigating the need for trade-offs in operations strategy. *Production and operations management*, 11(1), 9-20.

Braglia, M., Zanoni, S., & Zavanella, L. (2003). Measuring and benchmarking productive systems performances using DEA: an industrial case. *Production Planning & Control*, *14*(6), 542-554.

Brown, S., Bessant, J. R., & Lamming, R. (2013). Strategic operations management. Routledge.

Bulak, M. E., & Turkyilmaz, A. (2014). Performance assessment of manufacturing SMEs: a frontier approach. *Industrial Management & Data Systems*, 114(5), 797-816

Chambers, S., Johnston, R., & Slack, N. (2004). Operations Management. Pearson Education UK.

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

Chen, Y. S., & Chen, B. Y. (2011). Applying DEA, MPI, and grey model to explore the operation performance of the Taiwanese wafer fabrication industry. *Technological forecasting and social change*, 78(3), 536-546.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer.

Cook, W. D., Tone, K., & Zhu, J. (2014). Data envelopment analysis: Prior to choosing a model. *Omega*, 44, 1-4.

Deng , J . L ., (1982). Control problems of Grey Systems. Systems and Control Letters 5(2), 288-294

Düzakın, E., & Düzakın, H. (2007). Measuring the performance of manufacturing firms with super slacks based model of data envelopment analysis: An application of 500 major industrial enterprises in Turkey. *European Journal of Operational Research*, 182(3), 1412-1432.

Gardner, R. (2004). The process-focused organization: a transition strategy for success. ASQ Quality Press.

Hayes, R. H., & Wheelwright, S. C. (1984). Restoring our competitive edge: competing through manufacturing.

Hayes, R.H. and Wheelwright, S.C. (1985), "Competing through Manufacturing", Harvard Business Review, 99-109.

Iribarren, D., Martín-Gamboa, M., & Dufour, J. (2013). Environmental benchmarking of wind farms according to their operational performance. Energy, 61, 589-597

Jahanshahloo, G., Lotfi, F. H., Rostamy-Malkhalifeh, M., Maddahi, R., & Ebrahimnejad, A. (2013). Ranking non-extreme efficient units based on super efficiency method in the presence of undesirable outputs: a DEA approach. *International Journal of Applied Decision Sciences*, 6(1), 83-95.

Kaviani, M., Abbasi, M., Yusefi, M., & Zareinejad, M. (2014). Prioritizing operation strategies of companies using fuzzy AHP and importance-performance matrix. *Decision Science Letters*, *3*(3), 353-358.

Korhonen, P. (2002). Searching the efficient frontier in data envelopment analysis. In *Aiding Decisions with Multiple Criteria* (pp. 543-558). Springer US.

Le, T. N., Huang, Y. F., & Wang, C. N. (2014, June). The Selection of Strategic Alliance Partner in Vietnam Garment Industry Using Grey Theory and DEA. In *Computer, Consumer and Control (IS3C), 2014 International Symposium on*(pp. 673-676). IEEE.

Li, G. D., Yamaguchi, D., & Nagai, M. (2007). A grey-based decision-making approach to the supplier selection problem. *Mathematical and computer modelling*, 46(3), 573-581.

LI, Q., & LIN, Y. (2014). Review paper: A Briefing to Grey Systems Theory. *Journal of Systems Science and Information*, 2(2), 178-192.

Liedtka, J. M. (1998). Strategic thinking: can it be taught?. Long range planning, 31(1), 120-129.

Liu, C. H., Lin, S. J., & Lewis, C. (2010). Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis. Energy policy, 38(2), 1049-1058.

Liu, S., Fang, Z., & Forrest, J. (2010, October). On algorithm rules of interval grey numbers based on the "Kernel" and the degree of greyness of grey numbers. In *Systems Man and Cybernetics* (SMC), 2010 IEEE International Conference on (pp. 756-760). IEEE.

Meenakumari, R., Kamaraj, N., & Thakur, T. (2009). Measurement of relative operational efficiency of SOEUs in India using data envelopment analysis. *International Journal of Applied Decision Sciences*, 2(1), 87-104.

Memon, M. A., & Tahir, I. M.(2012), Company Operation Performance Using DEA and Performance Matrix: Evidence from Pakistan.

- Nath, P., Nachiappan, S., & Ramanathan, R. (2010). The impact of marketing capability, operations capability and diversification strategy on performance: a resource-based view. Industrial Marketing Management, 39(2), 317-329.
- Rahimnia, F., Moghadasian, M., & Mashreghi, E. (2011). Application of grey theory approach to evaluation of organizational vision. *Grey Systems: Theory and Application*, *1*(1), 33-46.
- Sarmiento, R., Byrne, M., Contreras, L. R., & Rich, N. (2007). Delivery reliability, manufacturing capabilities and new models of manufacturing efficiency. *Journal of Manufacturing Technology Management*, 18(4), 367-386.
- Seiford, L. M., & Thrall, R. M. (1990). Recent developments in DEA: the mathematical programming approach to frontier analysis. *Journal of econometrics*, 46(1)
- Shuai, J. J., & Wu, W. W. (2011). Evaluating the influence of E-marketing on hotel performance by DEA and grey entropy. *Expert systems with applications*, 38(7), 8763-8769.
- Skinner, W. (1969). *Manufacturing-missing link in corporate strategy* (pp. 136-145). Harvard Business Review.
- Slack, N., & Lewis, M. (2008). Operations Strategy. Harlow: Prentice Hall Financial.
- Slack, N., & Lewis, M. (2011). Operating Strategy.
- Slack, N., Chambers, S., Johnston, R., & Betts, A. (2006). Operations and Process Management: Principles and Practice for Strategic Impact. Pearson Education
- Sun, C. C. (2011). Evaluating and benchmarking productive performances of six industries in Taiwan Hsin Chu Industrial Science Park. *Expert Systems with Applications*, *38*(3), 2195-2205.
- Talluri, S., Vickery, S. K., & Droge, C. L. (2003). Transmuting performance on manufacturing dimensions into business performance: an exploratory analysis of efficiency using DEA. *International Journal of Production Research*, 41(10), 2107-2123.
- Wang, Q., Wang, S., & Wang, X. (2009, November). Research on total factor energy efficiency in China based on super efficiency grey DEA model. In *Grey Systems and Intelligent Services*, 2009. *GSIS* 2009. *IEEE International Conference on* (pp. 1542-1547). IEEE.
- Wang, S., Ma, Q., & Guan, Z. (2007, November). Measuring hospital efficiency in China using grey relational analysis and data envelopment analysis. In *Grey Systems and Intelligent Services*, 2007. GSIS 2007. IEEE International Conference on (pp. 135-139). IEEE.
- Wang, J., & Liu, S. (2012). Efficiency measures in DEA with grey interval data under the hypotheses of data consistency. *Grey Systems: Theory and Application*, 2(1), 63-69.
- Xia, D. C., Li, B. T., Wang, J. P., & Shi, G. P. (2014, August). Research on General DEA Model Based on the Grey Linear Programming. In Applied Mechanics and Materials (Vol. 577, pp.

828-831).

Xu,H. Zhou, SH. (2013). A grey data envelopment analysis model. *Journal of Theoretical and Applied Information Technology*, 48(3), 1992-8645.

Yang, Y. S. (1998). Data Envelopment Analysis (DEA) Model with Interval Gray Numbers. *International journal of information and management sciences*, 9, 11-24.

Zareinejad, M., Kaviani, M., Esfahani, M., & Masoule, F. (2014). Performance evaluation of services quality in higher education institutions using modified SERVQUAL approach with grey analytic hierarchy process (G-AHP) and multilevel grey evaluation. *Decision Science Letters*, *3*(2), 143-156.