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Eco-Efficiency Evaluation in Two-Stage Network Structure: Case Study: Cement Companies

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Abstract

The cement industry, as a primary trade, plays an important role in the development of a country's organization. This industry in Iran, however, despite of profuse benefits such as high-value mines, faces many challenges. Problems such as exploitation of the production require the need for doing research into this area. The main purpose of this paper is to examine the Eco-efficiency in Iran's 22 local cement companies over 2012-2016. This paper develops a Charnes, Cooper & Rhodes input oriented (CCRIO) Data Envelopment Analysis (DEA) approach for measuring the efficiency of decision processes which can be separated into two stages. The first stage uses its specific inputs to produce outputs, which parts of them are consequently considered as the inputs of the second stage. The first stage is considered as the production stage and the second stage as the pollution control stage. A novel converting two-stage to one stage model is proposed to obtain the Eco-efficiency. Consequently, Malmquist productivity index (MPI) is computed to assess productivity. Although DEA is a respected method for evaluating, it fails to extract unknown information. In this study data mining decision tree and Apriori algorithms are used to extract hidden rules, and to remove unrelated data.

Keywords:
Data Envelopment Analysis
Data Mining
Malmquist Productivity Index
Decision Tree
Apriori Algorithm
Two Stage Model

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INTRODUCTION

Data Envelopment Analysis (DEA) has been generally used for computing energy consumption, environmental efficiency, and eco-efficiency since it was initially suggested. The decision tree is one of the special data mining classification method. This predictive modeling technique customs a specific split-master way to divide the problem exploration space into subclasses. Apriori algorithm is association rules mining in numerous item sets. The major values of this concept are the divisions of common item sets and the supersets of uncommon data. This theory is regarded as the most typical data mining theory (Yuan et al., 2007). The concept of eco-efficiency derives from diverse implications. We describe eco-efficiency, in an effective way, as the capacity to yield belongings or facilities by saving energy, and resources or by decreasing waste and emissions. To find the unidentified trends in cement companies, all the accessible companies datasets are applied to an exclusive model and their DMUs efficiency are compared. A dataset for 22 companies with one input, two intermediate products, and one output after converting two-stage to proposed single stage model is used. Malmquist Productivity Index (MPI) in DEA model which is Charnes, Cooper & Rhodes Input-oriented (CCR_{IO}) to test and justify the alterations between companies is applied. The use of DEA as a decision analysis tool is limitless in literature, because DEA does not focus on finding a universal relationship for all units under assessment in the sample. DEA authorities every unit in the data to have its own production function, and then it estimates the efficiency of that single unit by comparing it to the efficiency of the other units in the dataset. After running the DEA model in DEA SOLVER software with every unit in the data, DEA classifies all units into two efficient (with more than one efficiency scores), and inefficient (with less than one efficiency scores) groups. After applying DEA inputs, outputs, and classes in data mining WEKA software, data mining decision tree algorithm is able to handle a diversity of data and capable to process datasets that might have errors and missing values. The concept of effective use of productivity properties in DEA, and prediction classification algorithms in data mining can improve the capacity of the companies, and it can solve the potential problem.

LITERATURE REVIEW

As a result of growing worries about the subject of energy safety and global warming, the problem of energy efficiency has gained significant attention from researchers. Consistent with the International Energy Agency (IEA, 2011), “Energy efficiency is a way of handling and confining the growth in energy consumption. Something is more energy efficient if it delivers more services for the same energy input, or the services for less energy input”. Throughout the last years, energy politicians have been continuing focuse on energy efficiency development and numerous studies have emphasized the significance to progress energy efficiency. This section offers a summary of previous computational educations on sketch acknowledgment in companies. Not only are diverse models lectured, but also several company inputs, and outputs are enclosed to have a rational judgment. In conclusion, the gap in the present literature, which was the key motivation of this study is also delivered. Some of the vital studies are introduced:

Ghulam and Jaffry (2015), applied the MPI to study productivity in cement companies in Pakistan. Their results revealed that privatization and lower degrees of governmental intervention in such companies had a progressive effect on the companies’ productivity. This development was connected with the permanency of political conditions, the improvement of the economic status, and an increase in effectiveness. Zhang et al. (2015), using the MPI, evaluated the performance of events containing $Co2$ in the transportation industry in China. The exploration took place in several time periods, showing that the performance of the Chinese transportation industry had dropped by 32.8%. This lessening of performance was attributed to a low level of technology in the field. Junfei et al. (2016), emphasize on the eco-efficiency study of Chinese provincial-level regions, concerning each region as a two-stage network configuration. The first stage is considered as the production system and the second stage is reflected in the pollution control system. Regarding the pollution emissions as intermediate products, a two-stage DEA model is suggested to attain the eco-efficiency of the entire two-stage structure. Alinezhad. (2016), proposed the combined form of DEA, and classification and regression technique rather than using DEA alone. Although DEA is a valuable method for benchmarking, it fails to give any perfect directions as to which process should be improved first. The suggested tactic enables firm's administrator to discover inefficient service units in a firm-level and inefficient processes in a facility unit-level.

Thus, pattern recognition in companies can be addressed through different computational, and combinatorial models. Regarding ranking and assessing firm's efficiency, other works, focused on diverse aspects of models can be mentioned: Baltskiy et al. (2016); Bian et al., (2016); Moya et al. (2016); Hejazi et al. (2017), Li et al. (2016) and Alinezhad and Mirmozaffari (2018). Also, different computational DEA and data mining techniques for various issues have been proposed by Mirmozaffari et al. in (2017a-2017b-2017c-2017d-2017e-2017f). Asgari Gashteroodkhani(2015), has used a DEA based method for fault section estimation and evaluated its performance on several scenarios.

It is perceived numerous DEA, and data mining models are frequently utilized in different studies to compare, rank, analyse and evaluate efficiency. As an example, Asgari Gashteroodkhani et al. (2019) have proposed a data- mining based method for fault location in transmission lines and improved the results by using an optimization algorithm. Consequently, a comprehensive comparison of diverse efficiency practically delivers an insight into firm's performances. This comparison is of great significance to energy practitioners who desire to evaluate Eco-efficiency at a proper step of its progression. A unique converting two-stage to one stage model in MPI is applied which eventually results in comparing various efficient and inefficient DMUs. Finally, applying decision tree and Apriori algorithm developed to operate on a specific database containing numerous transactions and it permits the managers to select which process to improve first.

DATASET DESCRIPTION

The standard dataset, collected in this study covers 5 periods (2012-2016), which is collected from 22 companies. So, an input of stage one, two intermediate elements, and an output of the second stage for the first company which is 2011 to 2016 are presented in Table 1.

Table 1: The Inputs, Intermediate elements and outputs for 1ST DMUs

Period	Input	Intermediate elements		Output
Year	**Energy consumption** (10 TCE)	**Cement production** (1 ton)	**Pollution control investment** (1000 RMB)	**Waste material removed** (100 kg)
2012	1063116	730865	80000	107237
2013	1425490	1216569	144000	289883
2014	1965650	1560395	144000	254899
2015	2539977	1861560	144000	264522
2016	2805942	2008740	144000	381952

consumptions in the companies are the only input in the first stage. Cement production (is outputs of stage one) and pollution control investments (is inputs of stage two) are two intermediate elements. Waste material removed in companies is the only output in the second stage.

RESEARCH METHODOLOGY

The objective of this study after converting two-stage to one stage, is to effectively compare companies' efficiency. Using a comparative DEA with MPI methodology a predictive data mining decision tree model with Apriori algorithm was developed to determine the characteristics of cement companies in terms of some DMUs and extracted rules. In general, the entire course can be divided into three stages as follows:

The CCR model

The CCR models reflect a steady or constant return to scale (CRS). Actually, a proportional rise in altogether inputs outcomes is set to the connected growth in outputs. The efficiency of a certain DMU is considered by means of the CCR model as follows:

$$\begin{aligned} & Min\ \theta_p \\ & s.t. \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{ip} && i = 1, \dots, m \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rp} && r = 1, \dots, s \\ & \lambda_j \ge 0, j = 1, \dots . n \end{aligned} \tag{1}$$

Where θ_p indicates the technical efficiency score of units DMU, λ_j represents the dual variables that pinpoint the benchmarks for inefficient units. If θ_p is set to one, then the measured DMU is considered technically efficient. In fact, it lies on the efficiency frontier, and it is collected from the set of efficient units. Except associating efficiency through DMUs in an organization, DEA has also been used to compare efficiency across companies. There are a number of types of DEA with the most basic being CCR based. In this study nonlinear, linear and dual specific CCR input oriented model are proposed.

PROPOSED MODEL

The proposed model can be divided into four steps as follows:

A new approach in DEA two-stage model

In current years, Chen et al. (2004); Kao et al. (2008); Chen et al. (2009a); Chen et al. (2009b); Wang et al. (2010) Hosseinzadeh lotfi et al. (2012); Adli Aminuddin et al. (2017) and Li et al. (2017) proposed various solutions concerning the two-stage model. A novel converting two-stage model to single stage model has been proposed in this study, and DMUj ($j=1,\dots,n$), X_{ij} ($i=1,\dots,m$) is energy consumption or input of the first stage, Y_{rj} ($r=1,\dots,s$) is waste material removed or output of the second stage, M_{hj} ($H=1,\dots,h$) is cement production or desirable output of the first stage, and N_{cj} ($C=1,\dots,c$) is pollution control investment or desirable input of the second stage.

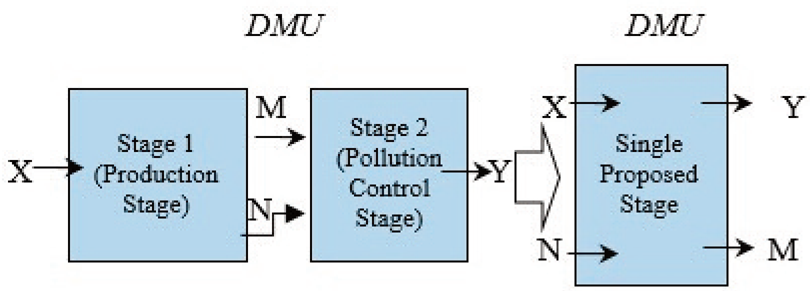

Fig. 1. Conversion of two-stage model to one-stage model

Fig.1 particularizes the proposed model. The two-stage model is reflected as a single stage, where the intermediate elements depending on being desirable or undesirable, are considered as part of final desirable outputs or desirable inputs in the proposed single stage model. An input, two intermediate elements, and an output are denoted by X, M or N, and Y. N is desirable inputs in the intermediate element, and in order to become minimize in the input-oriented model, treats like X, as desirable inputs. On the other hand, M is desirable output in intermediate element. In order to increase or to become constant in the input-oriented model, treats like Y, as desirable outputs. Finally, CCRIO, is widely discussed below:

Nonlinear single stage proposed model in CCR_{IO}:

$$Max\left(\sum_{r=1}^{S} u_r y_{rp} + \sum_{h=1}^{H} e_h m_{hp}\right) \Big/ \left(\sum_{i=1}^{m} v_i x_{ip} + \sum_{c=1}^{C} f_c n_{cp}\right)$$

$$s.t.\quad \left(\sum_{r=1}^{S} u_r y_{rj} + \sum_{h=1}^{H} e_h m_{hj}\right) \Big/ \left(\sum_{i=1}^{M} v_i x_{ij} + \sum_{c=1}^{C} f_c n_{cj}\right) \le 1$$

$$u_r, v_i, e_h, f_c \ge \varepsilon\ , j = 1, \ldots . n \tag{2}$$

Linear single stage proposed model in CCR_{IO}:

$$Max \sum_{r=1}^{S} u_r y_{rp} + \sum_{h=1}^{H} e_h m_{hp}$$

$$s.t. \sum_{i=1}^{m} v_i x_{ij} + \sum_{C=1}^{C} f_c n_{cj} = 1$$

$$\sum_{r=1}^{S} u_r y_{rj} + \sum_{h=1}^{H} e_h m_{hj} - \sum_{i=1}^{M} v_i x_{ij} - \sum_{c=1}^{C} f_c n_{cj} \le 0$$

$$u_r, v_i, e_h, f_c \ge \varepsilon\ , j = 1, \ldots . n \tag{3}$$

Dual single stage proposed model in CCR_{IO}:

$$Min\ \theta_p$$

$$S.t. \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_p x_{ip} \qquad i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j n_{cj} \le \theta_p n_{cp} \qquad c = 1, \ldots, C$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rp} \qquad r = 1, \ldots, s$$

$$\sum_{j=1}^{n} \lambda_j m_{hj} \ge m_{hp} \qquad , h = 1, \ldots, H$$

$$\lambda_j \ge 0,\ \theta_p\ free \tag{4}$$

Evaluation in combining MPI, and decision tree with apriori algorithms

The MPI is calculated to assess productivity growth relative to a reference technology. Two foremost issues are addressed in the computation of MPI growth. The first issue is the quantity of productivity change over the period, while the second is to decompose changes in productivity into what are generally denoted to as a 'catching-up' result or technical efficiency change (TEC), and a 'frontier shift' result or technological change (TC). MPI assesses the total factor productivity change of a DMU between two periods. The idea of productivity usually referred to as labor productivity, this concept is related to TFP, defined as the product of efficiency change (catch-up), and technological change (frontier-shift). If TFP value is more than one this indicates a positive TFP growth from period (t) to period (t+1), whereas a value less than one indicates a decrease in TFP growth or performance relative to the previous year. The frontier obtained in the current (t) and future (t+1) time periods are labeled. When inefficiency exists, the relative movement of any given DMU over time will therefore depend on both its position relative to the corresponding frontier (technical efficiency), and the position of the frontier itself (technical change), In fact

Malmquist Productivity Index (MPI) = TEC TC (5)

The decision tree is capable to produce comprehensible rules, and it has the capability to noticeably designate the best field. The C4.5 algorithm for the structure of decision trees is applied in WEKA as a classifier named J48.

Apriori is an easy-to-implement, and easy-to-comprehend algorithm. It can be used on large item sets, and it supports the managers in purchasing their item with more comfort which increases the sales and benefits of companies. In a more detail discussion Fig. 2 particularizes the proposed combining method.

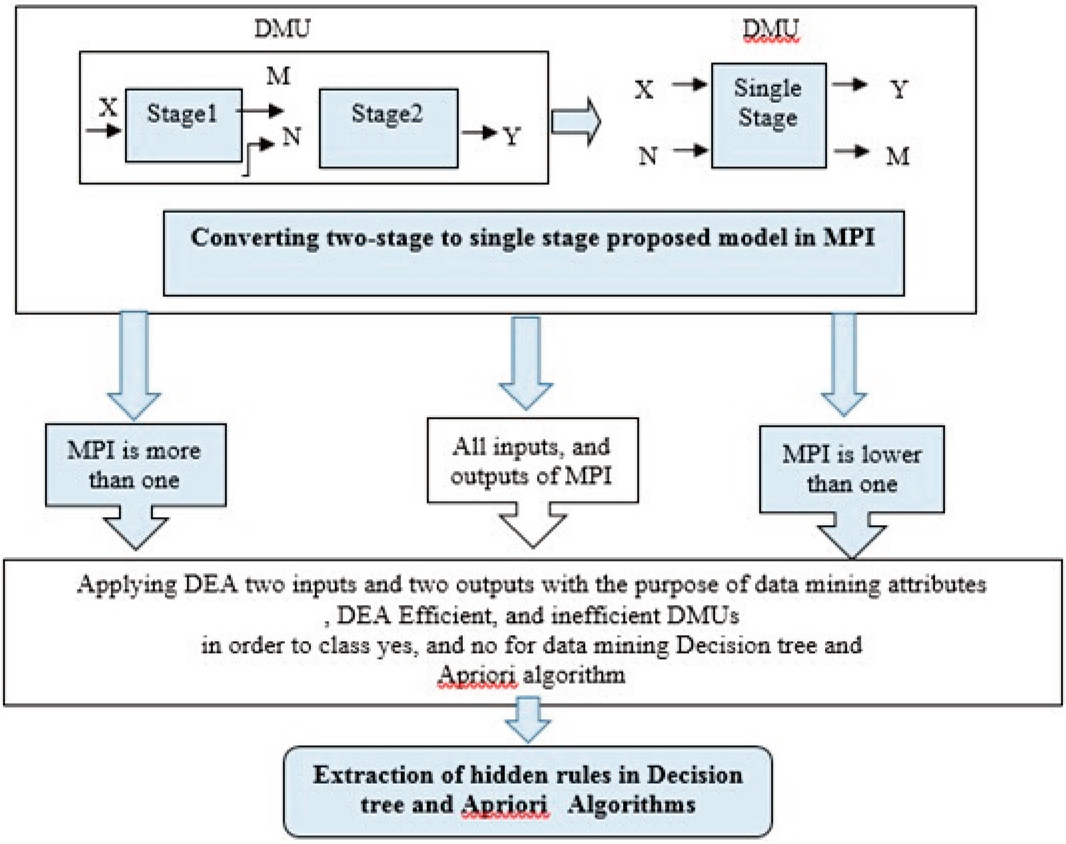

Fig.2.Implementation of combining DEA and data mining

RESULT AND DISCUSSION

The data covers in this study is a five-year span from 2012 to 2016 for 22 local cement companies. The proposed CCRIO is applied. Considering the number of DMUs is equal to N, and the time period is equal to T, the parameters of this study are 22(N), and 5(T), respectively. The average MPI of 22 cement companies during the years 2012-2016, based on aforementioned inputs, and outputs are given in Fig 3 and Table 2. In Fig 3, the order from 1st company to 22nd company is from left to right.

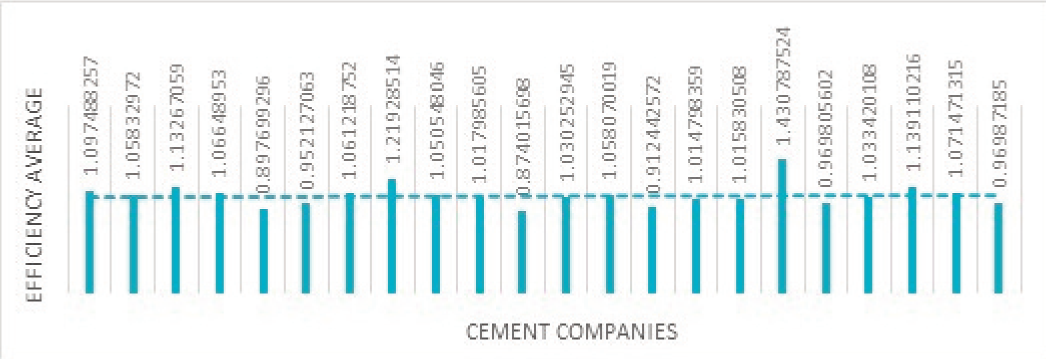

Fig. 3. Average efficiency over 5 year periods for 22 DMUs

Table 2: Productivity Measurement Results Based on MPI for 22 companies

Companies	MPI	Ranking
1	1.097	5
2	1.058	10
3	1.133	4
4	1.066	7
5	0.898	21
6	0.952	19
7	1.061	8
8	1.219	2
9	1.051	11
10	1.018	14
11	0.874	22
12	1.030	13
13	1.059	9
14	0.912	20
15	1.015	16
16	1.016	15
17	1.431	1
18	0.970	18
19	1.033	12
20	1.139	3
21	1.071	6
22	0.971	17

The efficiency process for 22 companies is presented in Fig 3. The horizontal axis represents the cement companies, and the vertical axis represents the average efficiency scores. As shown in Fig. 3, and table II the 17th company has the highest efficiency score and the 11th company has the lowest DMU efficiency score. The efficiency amount of 5th, 6th, 11th, 14th, 18th, and 22nd companies decreased over the 5 years period. The numeric attributes used in the data mining algorithms in this study which were decision tree and Apriori Algorithms include energy consumption, cement production, pollution control investment, and waste material removed. The MPI efficiency score is the class of data mining algorithms. DMUs with the MPI status greater than one are characterized with "yes" and DMUs with the MPI status of less than one are designated with "no". It is essential that the validity of the proposed method is evaluated in each study. To confirm the validity of the proposed model, and to test the authority of this research, data were divided into two groups, test data, and educational data in data mining algorithms. With this method, the final outputs are reviewed, and the validity of the research is verified. In this study, 70% of the data was designated as training data sets, and 30% of the data were selected as experimental data sets. In order to randomly select the experimental data, the Excel software has been used. According to aforesaid points, the data covers in this study is a five-year span from 2012 to 2016 (or T) for 22 local cement companies (or N). In fact, 110 ((N or 22 multiplied by T or 5 is 110)) separate inputs, outputs and classes are applied in WEKA software. The extraction of data mining decision tree and Apriori algorithm's rules can be divided into two stages as follows:

Extraction of decision tree's rules

The decision tree in this study is drawn by the j48 algorithm. This algorithm, arrange the data and then select the worth values for all cases where it is possible to separate these sorted data, and select the separator corresponding to the greatest usefulness of the value as a separator. One of the intrinsic features of a tree is the removal of some of the attributes based on the importance or minimum correlation. In the proposed decision tree model, the cement production attribute is eliminated. Figure 4 shows the j48 decision tree obtained from the implementation of the model. According to Fig. 4, J48 decision tree algorithm derived from the classification, and it is observed that companies are divided into two groups based on the amount of waste material removed. Companies with more than 228364 waste material removed, and companies with less than or equal to 228364 waste material removed. Companies with more than 228364 waste material removed are efficient. For a waste material removed of less than or equal to 228364, the pollution control investment is divided into two branches based on the pollution control investment of more than 210000, and pollution control investment of less or equal to this amount. Companies with more than 210000 pollution control investment are inefficient. For a pollution control investment of less than or equal to 210000, the energy consumption is divided into two branches based on the energy consumption of more than 578009, and energy consumption of less or equal to this amount. Companies with more than 578009 energy consumption are efficient. Companies with less or equal to 578009 energy consumption are inefficient.

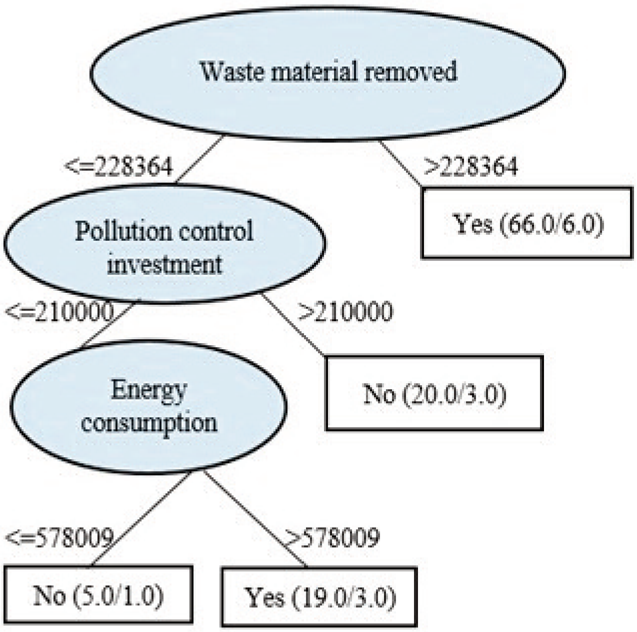

Fig. 4. Decision tree derived from the proposed model

This proposed model assesses the performance of each decision maker. In fact, this model not only does the function of other decision-makers, but also it uses the function of the same decision maker in the past.

Extraction of apriori algorithm's rules

After entering the attributes, and class by the WEKA software, Apriori algorithm in association rules is used. To select remarkable rules from the set of all possible rules, restrictions on several methods of importance, and interest are used. The best-known restrictions are minimum inceptions on support, and confidence. Support is a symptom of how repeatedly the item set appears in the dataset. For example, the rule has a support of one in a data set, since it occurs in 100% of all transactions (one out of one transaction). Confidence is a symptom of how often the rule has been found to be accurate. For instance, the rule has a confidence of one in a data set, since for 100% of the transactions the rule is correct. If the rule had a lift of one, it would suggest that the prospect of existence, and the resulting are independent of each other. When two processes are independent, no rule can be drawn linking those two events. If the lift is more than 1, two processes are independent on one another, and makes those rules potentially valuable for predicting the subsequent in upcoming data sets. Under this condition that the lift is larger than one, the greater the support, and confidence of a rule in Apriori algorithm, the higher it signifies a fixed configuration in the dataset. If these procedures are comparatively small, then any irregularity would be less strong than it would be for rules with high confidence, high support, and high lift. After applying aforementioned separate data sets, association rules are evaluated, and strong rules are extracted. In fact, extraction of strong rules can help practitioners, and cement firm's manager can have a better evaluation. These rules serve as a useful tool for researchers to effectively predict uncertain cases, and guide accordingly. In a more detail discussion of aforementioned conditions, three strong rules are presented in step 1, 2, and 3:

(1) Step 1 (strong rules with "min support": 0.25, and "min confidence": 0.9):

In step 1, only one rule with "min support" (0.25) is assessed. In fact, when "min confidence" is 0.9, the highest support is (0.29), and there is only one support higher than 0.25. This rule is applied as follows:

(a) Waste material removed = „(-inf-134031.2]" 33 ==> Cement production =„(-inf- 1964358.9]" 32

(Conf: 0.97, lift: 1:39)

According to the first strong rule (sup:0.29, Conf: 0.97, lift: 1.39) in step A, if waste material removed within the specified range occurs 33 times (33 out of 110), cement production within the specified range will happen 32 times (32 out of 110).

(2) Step 2 (strong rules with "min support": 0.2, and "min confidence": 0.9):

In step 2, only two rules with "min support" (0.2) are assessed. Since there is only one support (0.22) between 0.2, and 0.25. The first rule is the same one in step A. This rule is applied as follows:

(a) Energy consumption= „(952956.9-1549684.8]" 26 ==> Cement production =„(-inf- 1964358.9]" 24

(Conf: 0.92, lift: 1:32)

According to the second strong rule (sup:0.22, Conf: 0.92, lift : 1.32) in step B, if energy consumption within the specified range occurs 26 times (26 out of 110), cement production within the specified range will happen 24 times (24 out of 110).

(3) Step 3 (strong rules with "min support": 0.17, and "min confidence": 0.9):

In step C, only three rules with "min support" (0.17) are assessed. Because there is only one support (0.18) between 0.17, and 0.2. The first, and the second rules are the same rules in step A, and B. This rule is applied as follows:

(a) Waste material removed in inefficient DMUs= „(-inf-134031.2]" 20 ==> Cement production =„(-inf- 1964358.9]" 20

(Conf: 1, lift: 1:43)

According to the third strong rule (sup:0.18, Conf: 1, lift: 1:43) in step C, if energy consumption in inefficient DMUs within the specified range occurs 20 times (20 out of 110), cement production within the specified range will happen 20 times (20 out of 110).

CONCLUSION

An exclusive model which consists of replacing the two-stage model with a new single stage model, and merging MPI with decision tree and Apriori algorithm is introduced. Along with the results obtained from efficiency analysis, the managers of the 17th cement company have the highest efficiency in cement production centers during the five years period. They should try to have better efficiency in the future. Managers of other companies with less efficiency need to use specific data mining association rules strategy to enhance their efficiency. According to the proposed approach, based on the geometric average, results, and predictions derived from the time period in MPI, can assist as a practical instrument for the general practitioner to effectively compare the efficiency of uncertain cases. The presentation of the proposed method provides us with a chance to identify pattern recognition of the complete combining DEA and data mining techniques during the selected period of time (five years over 2012-2016). In conclusion, it is worth announcing the limitations of this paper. The most important limitation is connected with the inadequate contemplation of undesirable output. The current study measured only pollution control investment as undesirable output produced by the cement industry and special aforementioned approaches have been proposed to decrease this undesirable outputs, however there are other serious undesirable outputs which also could have been combined into the analysis if dependable data were accessible. Containing these variables may affect the efficiency marks of this study. However, the general inference remains the same as the proposed combining method in this study, can put up several inputs and outputs.

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