(CASE REPORT)

Sustainable performance analysis and ranking of organizations through fuzzy multi-criteria group decision making - A case study

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Abstract

In this paper, a decision support methodology for multiple attributes group decision making problem is developed. The proposed methodologies are based on Data Envelopment Analysis (DEA), Grey Relation analysis (GRA) and hybrid GRA-DEA methods. These methods are implemented for evaluation and ranking of organizations in sustainable perspective. In the proposed methods, the payoff values of alternatives are expressed in linguistic terms, given by the decision makers. Then, these linguistic terms are described by triangular fuzzy numbers. Charnes model of DEA is formulated in fuzzy environment to determine efficiencies of DMUs. Following the GRA method's algorithm, a relative closeness coefficient is defined to determine the ranking order of all alternatives by calculating the distances to the fuzzy positive-ideal solution (FPIS), as well as to the fuzzy negative-ideal solution (FNIS). Also, performance evaluation of these companies is made through hybrid GRA-DEA in fuzzy environment. The weights of the criteria are determined objectively during evaluation of these companies in the proposed GRA and DEA-GRA methods. Comparison of proposed approaches is made and final ranking of the organizations is sustainable perspective is arrived. The proposed methodologies are illustrated with a case study of five steel manufacturing companies in India.

Keywords: Sustainable performance; Categorical regression analysis; Grey relation analysis; Multi criteria decision making

1. Introduction

It is now widely accepted that manufacturing organizations have a vital role to play in the quest for sustainability. Manufacturing organizations consume significant amounts of resources and generate waste. On a global scale, the worldwide energy consumption of manufacturing industries is growing continuously and are responsible for global carbon dioxide (CO_2) emissions. The companies need to adopt sustainable manufacturing practices (SMPs) to use the raw material effectively, by creating new product through current technology, regulatory measures and coherent social behaviours with respect to the triple bottom line performance. SMPs include the relevant environmental issues, green manufacturing, lifecycle aspects, and in advancing manufacturing operations and processes. SMPs focused on environmental, economic, and social sustainability as important drivers for sustainable manufacturing. SMPs emphasize to minimize the manufacturing operations in order to optimize production efficiency of firms.

The intensity of global interest and ever-increasing sustainability importance has led organizations to search for more efficient and effective ways to manage their business operations towards sustainability. Measuring the performance of

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business processes has become a central issue in both academia and business, since organizations are challenged to achieve effective and efficient results in sustainable perspective. Applying performance measurement models to this purpose ensures alignment with a business strategy, which implies that the choice of performance indicators is organization-dependent. Nonetheless, such measurement models generally suffer from a lack of guidance regarding the performance indicators that exist and how they can be concretized in practice.

In this context, a suitable evaluation of the companies' performance in sustainable perspective is critical not only for themselves but also for their own creditors and investors. The evaluation is one of the most important tools for identifying the internal strengths and weaknesses and determining the external opportunities and threats, and also can clarify the companies' position than other ones. Moreover, the evaluation-based information can be used by future investors and creditors for selecting companies for the investment and lending to them, respectively. Despite the high importance of performance evaluation, a few numbers of the methods have been developed in this context, including some conventional and simple methods. Here, the important issue in the evaluation is the development of multi-attribute/multi-criteria methods for ranking of organizations in sustainability perspective and the proposition of sustainable performance criteria.

The remainder of the paper is structured as follows. Section provides literature review on MCDM methods. In section 3 Multi-Criteria Decision making methods proposed in the study are discussed. Section 4 deals with Case study of 5 Steel manufacturing organizations and the criteria for performance evaluation under sustainable perspective. Section 5 analyzes results and ranking of the organizations is presented. Concluding remarks are made in section 6.

2. Literature review

Tomasz Thiel (2008) proposed the procedure to determine relative criteria importance to increase of reliability of calculations using MCDA method, where the relative importance of criteria is provided. Rajesh Kumar Singh et al., (2009) compiled the information related to sustainability indices formulation strategy, scaling, normalisation, weighting and aggregation methodology.

Alev Taskin Gumus et al., (2013) proposed a Buckley extension based fuzzy Analytical Hierarchical Process (Fuzzy-AHP) and linear normalization based fuzzy Grey Relational Analysis (Fuzzy-GRA) for hydrogen energy storage selection problem. Vanathi and (2014) extended hesitant fuzzy sets to Triangular Hesitant Fuzzy sets to determine the criteria weights for an example of the health hazard of traffic police to deal with imprecise or vague information effectively. Michael Mutingi et al., (2014) provided a structured approach to guide supply chain managers to develop effective performance management system for specific GSCM strategies.

Jesús Cuadrado et al., (2015) presented AHP method to serve as a sustainability-related decision-making tool in industrial building projects. Seyed Hossein et al., (2015) determined weights of criteria in MCDM problems and is illustrated by a numerical example for the selection of a maintenance strategy.

Frank Medel-Gonzáleza et al., (2016) studied sustainability performance measurement in Cuban organizations by combiningBalanced Scorecard and Analytic Network Process. Aldona Kluczek (2016) presented analytical hierarchy process to determine ranking of simple and relevant activity areas for manufacturing processes in terms of sustainability objectives. Celik. E, M. Erdogan and A. T. Gumus (2016) proposed combinationof fuzzy TOPSIS and GRA, to evaluate Five Turkish green 3PLs serving in Istanbul based on different separation measures using trapezoidal fuzzy numbers. Mohammad Sadegh Pakkar (2016) proposed integrated AHP-DEA-GRA method and is illustrated with an example of a nuclear waste dump site selection.

Praveen Prakash et al., (2017) presented multiple-criteria decision-making (MCDM) methodologies to evaluate and select the best sustainable supply chain management strategy using the AHP and the ANP. The authors believed that the users can learn much from AHP model and can gain enough insight about the problem before extending it to an ANP model. Pichat Sopadangn Sooksiri Wichaisri and Ruth Banomyong (2017) proposed sustainable supply chain performance measurement consists of three dimensions with 14 indicators to assess overall sustainability of the studied supply chain. Huang, Aihua (2017) developed index-and value-based methods for evaluating sustainable manufacturing performance for a case study of a consumer electronics enterprise. Abhishek et al., (2017) utilized AHP successfully to design a rural microgrid considering multiple criteria with various scenarios under sustainable development perspective.

Kumar Vijay et al (2019) discussed multi attribute group decision making and demonstrated the method by taking a hypothetical case study to rank the cancer treatments. Jaffar Abbas et al., (2019) made a study to investigate the

relationship of environmental effects, CSR, and social media marketing application to calculate the sustainable performance of business firms. Muhammad Waris et al., (2019) developed AHP framework to measure the sustainable procurement index values for the Malaysian construction industry. Alexandre André Feil et al., (2019) compiled set of factors as the backbone of sustainability indicators that can be expanded and reduced as needed by industry managers. Anquan Zou et al., (2019) developed a multicriteria analysis method for effectively making the selection decision on information systems (IS) projects for project management in organizations from a sustainability perspective.

Ioannis E. Tsolas (2019) proposed GRA-DEA approach for selecting the best utility exchange traded funds (ETFs) and concluded that the proposed method is superior to conventional DEA as regards the fund ranking. Chun-Ho Chen (2019) combined grey relational analysis (GRA) techniques with intuitionistic fuzzy entropy-based Technique for OrderPreference by Similarity to Ideal Solution (TOPSIS) method, to solve the supplier selection problem.

In this study, Data Envelopment Analysis (DEA), Grey Relation Analysis (GRA) and hybrid GRA-DEA methods are proposed and implemented for performance evaluation and ranking of steel manufacturing organizations in sustainable perspective

3. Multi-criteria decision making methods

Multi-criteria assessment model can be suitable in solving complex problems. In issues of multi-criteria decision making, decision makers choose the most suitable alternative after rational evaluation of a limited set of independent or interdependent linguistic judgement criteria. Fuzzy set theory has been widely used to solve problems related to multi-criteria decision making (MCDM). Grey system theory is a method to explore uncertainty in the case of scare data and has advantages in deductive analysis of uncertain information situation. It has been successfully applied to situations where there is partial information or uncertainty. GRA methodology has been applied to solve uncertainties in different fields under discrete data and incomplete information environment. GRA technique is one of the common methods for analyzing various relationships among discrete data sets and making the right decisions in the case of multiple criteria or attribute situations. The techniques first obtain a correlation between reference sequence and comparable sequences and then sort the alternatives according to the correlation.

In recent years, data envelopment analysis (DEA) has been widely used to evaluate the performance of organizations. The units under evaluation in DEA are called decision making units (DMUs) and their performance measures are grouped into inputs and outputs. DEA is non-parametric and doesnot require an explicit functional form relating inputs and outputs. In the current study, performance of listed steel manufacturing companies in sustainable perspective have been evaluated by using 1) Manufacturing Process factors, 2) Supply Chain Management factors, 3) Social Responsibility factors, 4) Environment Management factors, 5) Organizational performance factor. Increasing importance of sustainable performance evaluation of the companies, it requires a comprehensive ranking methodology for evaluation and ranking of organizations based on sustainable perspective.

Considering that the attributes have different importance degrees, the weighting vector of all attributes, given by the DMs, is obtained through a model based on the standard deviation of expected values from the triangular fuzzy decision matrix. Then by GRA approach and integrated GRA-DEA approach is implemented to evaluate and rank the organizations.

3.1. DEA Method

The CCR model is a fractional programming model, which measures the relative technical efficiency of a unit by calculating the ratio of weighted sum of its outputs to the weighted sum of its inputs. The fractional program is run for each unit to determine the set of input-output weights, which maximizes the efficiency of that unit, subjected to the condition that no unit can have a relative efficiency score greater than unity for that set of weights.

3.2. Grey Relation Analysis (GRA) Method

Grey relational analysis is a kind of method which enables determination of the relational degree of every factor in the system. It uses information from the grey system to dynamically compare each factor quantitatively, based on the level of similarity and variability among factors to establish their relation. GRA analyzes the relational grade for discrete sequences. In this study, GRA method is implemented in fuzzy environment using triangular fuzzy numbers. Relative weights of the criteria are obtained through CRITIC method.

3.3. GRA-DEA Method

In this thesis, optimistic and pessimistic DEA models are developed using grey relation coefficients. Pessimistic and optimistic DEA models developed by Mohammad Sadegh Pakkar, (2016) are extended in fuzzy environment to evaluate performance of alternatives in sustainable perspective. The alternatives are ranked by considering the normalized grey relation grade (Zhou et. al., 2007).

4. Case study

Performance evaluation of Steel manufacturing organizations based on sustainable perspective is made with a case study of five steel manufacturing Organizations in India. The names of the SMOs are not disclosed and named them as A1, A2, A3, A4 and A5. Features of these organizations are discussed below. In the study, 21 attributes under five criteria are considered for evaluation and ranking of steel manufacturing organizations based on sustainable perspective.

4.1. Criteria/Attributes of Sustainable Performance

4.1.1. Manufacturing process factor

Five attributes are considered under manufacturing process factor.

- Investment in Manufacturing Up gradation towards sustainability (C1)
- Design for sustainability (reuse, reduce, fewer and accessible) (C2)
- Energy efficient Renewable Sources (C3)
- Operational Safety and Personnel Health (C4)
- Monitoring of manufacturing process (minimize air emissions, waste creation, minimize hazardous outputs) (C5)

4.1.2. Supply chain management factor

Four attributes are considered under Supply chain Management factor.

- Supplier management (selection of Suppliers, Environmental collaboration, Use of 3 Rs) (C6)
- Green Logistics(Packaging, Transportation, Reverse Logistics-waste management) (C7)
- Life-cycle perspective coordination between product, process, and supply chain design(C8)
- Customer management(C9)

4.1.3. Social responsibility factor

Four attributes are considered under Social responsibility factor

- Training and development (C10)
- Promoting Employees' health and safety(C11)
- Work-life balance for employees (C12)
- Involvement in community Programs (C13)

4.1.4. Environment management factor

Four attributes are considered under Environment management factor

- Commitment of from senior managers (C14)
- Employee involvement(C15)
- Cross-functional cooperation and community involvement for environmental improvements(C16)
- Environmental compliance and auditing programs(C17)

4.1.5. Factors of organizational performance

Four attributes are considered under sustainable performance of the organization

- Green Image (C18)
- Improved profitability(C19)
- Better Asset Utilization (C20)
- Stronger competitive position(C21)

5. Results and discussion

Evaluation of performance based on sustainable perspective for a case study of five steel manufacturing organizations is carried out by adopting the proposed methods.

5.1. DEA Method

Discussions are made with three categories of decision makers namely: social scientists, pollution control board members and top executives of the organizations regarding sustainable attributes of the organizations. Evaluations of the attributes in the form of linguistic variables are collected from the decision makers. In the Fuzzy-DEA phase, the DMs are asked to evaluate alternatives considering each criterion. The linguistic scale and corresponding triangular fuzzy numbers are illustrated in Table 1.

Table 1 Linguistic variable and triangular fuzzy number

S.No.	Linguistic variable	Triangular fuzzy number
1	Very Low (VL)	(0,0,0.1)
2	Low (L)	(0,0.1,0.3)
3	Medium Low (ML)	(0.1,0.3,0.5)
4	Medium (M)	(0.3,0.5,0.7)
5	Medium High (MH)	(0.5,0.7,0.9)
6	High (H)	(0.7,0.9,1.0)
7	Very High	(0.9,1.0,1.0)

The ratings of each attribute with respect to the alternatives given by the three decision makers as a linguistic variable aregiven in Table 2.

Linguistic data is transformed into triangular fuzzy numbers. To avoid computational complexity in the decision-making process the aggregate fuzzy decision matrix is developed and presented in Table 3.

DEA methodology is implemented for evaluation and ranking of steel manufacturing organizations by solving the DEA model with triangular fuzzy inputs and outputs. A lingo code is developed to solve the basic DEA optimization model.

5.1.1. Ranking of steel manufacturing organizations

Ranking is done based on efficiency value of DMUs obtained in solving the optimization model in fuzzy environment. Efficiency of all the DMUs is obtained as 1.0000 indicates that all the DMUs are efficient. Hence the DEA method fails to distinguish the alternatives in the performance perspective.

5.2. GRA Method

Evaluation of performance based on sustainable perspective for a case study of five steel manufacturing organizations through GRA method and is illustrated below.

5.2.1. Relative weights of the attributes

In this study, weights of the attributes are obtained by establishing a weight model based on the standard deviation of expected values from the triangular fuzzy decision matrix using critic method. Expected Value of the attributes are determined and presented in Table 4.

Standard deviations of expected vales are determined and shown in Table 5.

Relative Weights of the attributes are determined and presented in Table 6.

5.2.2. Fuzzy normalized decision matrix

The fuzzy Normalized decision matrix for each criterion is determined and present in the Table 7.

5.2.3. Separation measures from positive and negative ideal solutions

Fuzzy positive and fuzzy negative ideal solutions are determined and separation measures from fuzzy positive and fuzzy negative ideal solutions are determined and are presented in Table 8 and 5.9 respectively.

5.2.4. Ranking of alternatives

Grey relation coefficient of each alternative from PIS and NIS is determined. Then grey relation grades are determined. From grey relation grades, closeness coefficients are determined and the alternatives are ranked in decreasing order of closeness coefficients. The ranking of alternatives is presented in Table 10.

From Table 10, it is observed that highest performance is obtained for A2 with closeness coefficient of 0.6360 and the lowest performance is obtained with A1 with closeness coefficient of 0.4290. The GRA method clearly distinguishes the performances of the alternatives.

5.3. Hybrid GRA-DEA Method

Evaluation of performance based on sustainable perspective for a case study of five steel manufacturing organizations through Hybrid GRA-DEA method is illustrated below.

5.3.1. Absolute differences

The absolute difference of the compared series and the referential series are obtained from weighted normalized fuzzy decision maytrix and are presented in Table 11.

5.3.2. Fuzzy grey relation coefficients

Fuzzy Grey relational coefficients are determined and the values are presented in Table 12.

5.3.3. Ranking of alternatives

Optimistic and pessimistic grey relation grades are obtained by solving the optimization problems using Lingo Code. Normalized grey relation grade is obtained from optimistic and pessimistic grey relation grades. Alternatives are ranked based on the descending order of normalized grey relation grade. Ranking of alternatives is presented in Table 13 and Comparison of ranking by GRA and Hybrid GRA-DEA is presented in Table 14.

From Table 13, it is observed that highest performance is obtained for A2 with normalized grey relation grade of 0.8094 and the lowest performance is obtained with A1 with normalized grey relation grade of 0.1906. The Hybrid GRA-DEA method also clearly distinguishes the performances of the alternatives.

From the obtained ranking of alternatives by GRA and hybris GRA-DEA methods, it is possible to make a conclusion that the alternative 'A2'is showing the highest performance, while the alternative 'A1'is showing the lowest performance in respect of sustainable perspective.

Table 2 Linguistic data of attributes of alternatives

Alternatives	DMs	Attributes																				
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21
A1	DM1	ML	VL	L	ML	ML	L	L	L	ML	L	L	L	L	ML	L	L	VL	ML	L	ML	VL
	DM2	ML	VL	L	VL	M	L	L	L	ML	ML	M	L	L	ML	ML	VL	L	L	L	L	ML
	DM3	M	ML	VL	M	M	ML	ML	VL	ML	ML	L	L	ML	ML	ML	VL	L	L	L	L	VL
A2	DM1	H	H	VH	VH	H	H	H	VH	H	H	H	H	VH	VH	H	VH	VH	VH	VH	H	VH
	DM2	VH	H	H	VH	H	H	VH	VH	H	H	VH	H	VH	VH	H	H	H	H	MH	H	H
	DM3	H	VH	MH	H	H	H	H	H	VH	H	MH	VH	MH	H	H	VH	H	H	VH	H	MH
A3	DM1	M	ML	ML	M	ML	ML	M	ML	M	ML	MH	M	MH	MH	MH	ML	M	M	M	MH	MH
	DM2	M	MH	M	MH	ML	ML	M	ML	ML	M	MH	MH	MH	MH	MH	MH	M	H	M	MH	MH
	DM3	M	MH	M	M	ML	ML	M	M	ML	M	M	M	ML	MH	M	ML	M	ML	MH	MH	MH
A4	DM1	H	ML	L	H	VL	VL	ML	M	ML	MH	ML	L	M	M	MH	M	MH	MH	VL	M	H
	DM2	L	MH	L	VH	VH	ML	M	ML	M	H	MH	MH	VL	ML	L	VH	MH	M	MH	MH	M
	DM3	MH	MH	M	H	ML	VL	VL	M	M	H	L	H	VL	H	ML	H	MH	MH	M	VL	VH
A5	DM1	MH	MH	M	MH	M	M	H	M	M	MH	M	H	H	MH	MH	MH	MH	MH	M	MH	MH
	DM2	MH	MH	MH	M	M	MH	MH	M	M	MH	MH	H	H	M	MH	MH	M	MH	MH	MH	MH
	DM3	MH	M	MH	M	H	MH	MH	H	M	MH	MH	M	M	M	MH	H	MH	MH	MH	MH	H

Table 3 Aggregate fuzzy data

Alternatives	Attributes																										
	C1			C2			C3			C4			C5			C6			C7			C8			C9		
A1	0.100	0.300	0.500	0.000	0.000	0.100	0.000	0.100	0.300	0.100	0.300	0.500	0.100	0.300	0.500	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.100	0.300	0.100	0.300	0.500
	0.100	0.300	0.500	0.000	0.000	0.100	0.000	0.100	0.300	0.000	0.100	0.300	0.300	0.500	0.700	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.100	0.300	0.100	0.300	0.500
	0.300	0.500	0.700	0.100	0.300	0.500	0.000	0.000	0.100	0.300	0.500	0.700	0.300	0.500	0.700	0.100	0.300	0.500	0.100	0.300	0.500	0.000	0.000	0.100	0.100	0.300	0.500
Agg Fuzzy Data	0.100	0.367	0.700	0.000	0.100	0.500	0.000	0.067	0.300	0.000	0.300	0.700	0.100	0.433	0.700	0.000	0.167	0.500	0.000	0.167	0.500	0.000	0.067	0.300	0.100	0.300	0.500

A2	0.700	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000
	0.900	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000
	0.700	0.900	1.000	0.900	0.900	1.000	0.500	0.700	0.900	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000
Agg Fuzzy Data	0.700	0.900	1.000	0.700	0.900	1.000	0.500	0.833	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000
A3	0.300	0.500	0.700	0.100	0.300	0.500	0.100	0.300	0.500	0.300	0.500	0.700	0.100	0.300	0.500	0.100	0.300	0.500	0.300	0.500	0.700	0.100	0.300	0.500	0.300	0.500	0.700
	0.300	0.500	0.700	0.500	0.700	0.900	0.300	0.500	0.700	0.500	0.700	0.900	0.100	0.300	0.500	0.100	0.300	0.500	0.300	0.500	0.700	0.100	0.300	0.500	0.100	0.300	0.500
	0.300	0.500	0.700	0.500	0.700	0.900	0.300	0.500	0.700	0.300	0.500	0.700	0.100	0.300	0.500	0.100	0.300	0.500	0.300	0.500	0.700	0.300	0.500	0.700	0.100	0.300	0.500
Agg Fuzzy Data	0.300	0.500	0.700	0.100	0.567	0.900	0.100	0.433	0.700	0.300	0.567	0.900	0.100	0.300	0.500	0.100	0.300	0.500	0.300	0.500	0.700	0.100	0.367	0.700	0.100	0.367	0.700
A4	0.700	0.900	1.000	0.100	0.300	0.500	0.000	0.000	0.100	0.700	0.900	1.000	0.000	0.100	0.300	0.000	0.000	0.100	0.100	0.300	0.500	0.300	0.500	0.700	0.100	0.300	0.500
	0.000	0.100	0.300	0.500	0.700	0.900	0.000	0.000	0.100	0.900	0.900	1.000	0.900	0.900	1.000	0.100	0.300	0.500	0.300	0.500	0.700	0.100	0.300	0.500	0.300	0.500	0.700
	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700	0.700	0.900	1.000	0.100	0.300	0.500	0.000	0.000	0.100	0.000	0.000	0.100	0.300	0.500	0.700	0.300	0.500	0.700
Agg Fuzzy Data	0.000	0.567	1.000	0.100	0.567	0.900	0.000	0.167	0.700	0.700	0.900	1.000	0.000	0.433	1.000	0.000	0.100	0.500	0.000	0.267	0.700	0.100	0.433	0.700	0.100	0.433	0.700
A5	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700	0.500	0.700	0.900	0.300	0.500	0.700	0.300	0.500	0.700	0.700	0.900	1.000	0.300	0.500	0.700	0.300	0.500	0.700
	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700	0.300	0.500	0.700
	0.500	0.700	0.900	0.300	0.500	0.700	0.500	0.700	0.900	0.300	0.500	0.700	0.700	0.900	1.000	0.500	0.700	0.900	0.500	0.700	0.900	0.700	0.900	1.000	0.300	0.500	0.700
Agg Fuzzy Data	0.000	0.567	1.000	0.300	0.633	0.900	0.300	0.633	0.900	0.300	0.567	0.900	0.300	0.633	1.000	0.300	0.633	0.900	0.500	0.767	1.000	0.300	0.633	1.000	0.300	0.500	0.700

Table 3 Aggregate fuzzy data (Contd..)

Alternatives	Attributes																	
	C10			C11			C12			C13			C14			C15		
Al	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.100	0.300	0.100	0.300	0.500	0.000	0.100	0.300
	0.100	0.300	0.500	0.300	0.500	0.700	0.000	0.100	0.300	0.000	0.100	0.300	0.100	0.300	0.500	0.100	0.300	0.500
	0.100	0.300	0.500	0.000	0.100	0.300	0.000	0.100	0.300	0.100	0.300	0.500	0.100	0.300	0.500	0.100	0.300	0.500

Agg Fuzzy Data	0.000	0.233	0.500	0.000	0.233	0.700	0.000	0.100	0.300	0.000	0.167	0.500	0.100	0.300	0.500	0.000	0.233	0.500
A2	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000
	0.700	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000
	0.700	0.900	1.000	0.500	0.700	0.900	0.900	0.900	1.000	0.500	0.700	0.900	0.700	0.900	1.000	0.700	0.900	1.000
Agg Fuzzy Data	0.700	0.900	1.000	0.500	0.833	1.000	0.700	0.900	1.000	0.500	0.833	1.000	0.700	0.900	1.000	0.700	0.900	1.000
A3	0.100	0.300	0.500	0.500	0.700	0.900	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900
	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900
	0.300	0.500	0.700	0.300	0.500	0.700	0.300	0.500	0.700	0.100	0.300	0.500	0.500	0.700	0.900	0.300	0.500	0.700
Agg Fuzzy Data	0.100	0.433	0.700	0.300	0.633	0.900	0.300	0.567	0.900	0.100	0.567	0.900	0.500	0.700	0.900	0.300	0.633	0.900
A4	0.500	0.700	0.900	0.100	0.300	0.500	0.000	0.100	0.300	0.300	0.500	0.700	0.300	0.500	0.700	0.500	0.700	0.900
	0.700	0.900	1.000	0.500	0.700	0.900	0.500	0.700	0.900	0.000	0.000	0.100	0.100	0.300	0.500	0.000	0.100	0.300
	0.700	0.900	1.000	0.000	0.100	0.300	0.700	0.900	1.000	0.000	0.000	0.100	0.700	0.900	1.000	0.100	0.300	0.500
Agg Fuzzy Data	0.500	0.833	1.000	0.000	0.367	0.900	0.000	0.567	1.000	0.000	0.167	0.700	0.100	0.567	1.000	0.000	0.367	0.900
A5	0.500	0.700	0.900	0.300	0.500	0.700	0.700	0.900	1.000	0.700	0.900	1.000	0.500	0.700	0.900	0.500	0.700	0.900
	0.500	0.700	0.900	0.500	0.700	0.900	0.700	0.900	1.000	0.700	0.900	1.000	0.300	0.500	0.700	0.500	0.700	0.900
	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700	0.300	0.500	0.700	0.300	0.500	0.700	0.500	0.700	0.900
Agg Fuzzy Data	0.500	0.700	0.900	0.300	0.633	0.900	0.300	0.767	1.000	0.300	0.767	1.000	0.300	0.567	0.900	0.500	0.700	0.900

Table 3 Aggregate fuzzy data (Contd..)

Alternatives	Attributes																	
	C16			C17			C18			C19			C20			C21		
A1	0.000	0.100	0.300	0.000	0.000	0.100	0.100	0.300	0.500	0.000	0.100	0.300	0.100	0.300	0.500	0.000	0.000	0.100
	0.000	0.000	0.100	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.100	0.300	0.100	0.300	0.500
	0.000	0.000	0.100	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.100	0.300	0.000	0.000	0.100

Agg Fuzzy Data	0.000	0.033	0.300	0.000	0.067	0.300	0.000	0.167	0.500	0.000	0.100	0.300	0.000	0.167	0.500	0.000	0.100	0.500
	0.900	0.900	1.000	0.900	0.900	1.000	0.900	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000
A2	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.500	0.700	0.900	0.700	0.900	1.000	0.700	0.900	1.000
	0.900	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.900	0.900	1.000	0.700	0.900	1.000	0.500	0.700	0.900
Agg Fuzzy Data	0.700	0.900	1.000	0.700	0.900	1.000	0.700	0.900	1.000	0.500	0.833	1.000	0.700	0.900	1.000	0.500	0.833	1.000
	0.100	0.300	0.500	0.300	0.500	0.700	0.300	0.500	0.700	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900
A3	0.500	0.700	0.900	0.300	0.500	0.700	0.700	0.900	1.000	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900
	0.100	0.300	0.500	0.300	0.500	0.700	0.100	0.300	0.500	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900
Agg Fuzzy Data	0.100	0.433	0.900	0.300	0.500	0.700	0.100	0.567	1.000	0.300	0.567	0.900	0.500	0.700	0.900	0.500	0.700	0.900
	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900	0.000	0.000	0.100	0.300	0.500	0.700	0.700	0.900	1.000
A4	0.900	0.900	1.000	0.500	0.700	0.900	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700
	0.700	0.900	1.000	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700	0.000	0.000	0.100	0.900	0.900	1.000
Agg Fuzzy Data	0.300	0.767	1.000	0.500	0.700	0.900	0.300	0.633	0.900	0.000	0.400	0.900	0.000	0.400	0.900	0.300	0.767	1.000
	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900
A5	0.500	0.700	0.900	0.300	0.500	0.700	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900
	0.700	0.900	1.000	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900	0.500	0.700	0.900	0.700	0.900	1.000
Agg Fuzzy Data	0.500	0.767	1.000	0.300	0.633	0.900	0.500	0.700	0.900	0.300	0.633	0.900	0.500	0.700	0.900	0.500	0.767	1.000

Table 4 Expected values of attributes

Alternatives	Attributes																				
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21
A1	0.400	0.167	0.083	0.311	0.400	0.217	0.217	0.083	0.300	0.217	0.317	0.133	0.217	0.300	0.217	0.083	0.083	0.217	0.217	0.217	0.167
A2	0.900	0.900	0.833	0.900	0.867	0.867	0.900	0.900	0.900	0.867	0.833	0.900	0.817	0.900	0.867	0.900	0.900	0.900	0.817	0.867	0.833
A3	0.500	0.500	0.400	0.600	0.300	0.300	0.500	0.400	0.400	0.450	0.600	0.600	0.500	0.700	0.600	0.500	0.500	0.556	0.600	0.700	0.700

A4	0.567	0.500	0.267	0.900	0.456	0.167	0.278	0.400	0.400	0.783	0.378	0.567	0.267	0.556	0.378	0.767	0.750	0.600	0.411	0.411	0.767
A5	0.700	0.600	0.600	0.600	0.683	0.600	0.783	0.683	0.500	0.700	0.633	0.744	0.683	0.600	0.700	0.783	0.600	0.700	0.600	0.700	0.700

Table 5 Standard deviations of attributes

Alternatives	Attributes																				
	Cl	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21
Al	0.046	0.134	0.125	0.123	0.020	0.046	0.102	0.168	0.040	0.150	0.055	0.208	0.078	0.097	0.113	0.274	0.234	0.143	0.097	0.131	0.218
A2	0.082	0.082	0.048	0.082	0.064	0.064	0.082	0.082	0.082	0.064	0.048	0.082	0.041	0.082	0.064	0.082	0.082	0.082	0.041	0.064	0.048
A3	0.013	0.013	0.046	0.000	0.098	0.098	0.013	0.046	0.046	0.027	0.000	0.000	0.013	0.008	0.000	0.013	0.013	0.003	0.000	0.008	0.008
A4	0.002	0.013	0.120	0.082	0.025	0.200	0.113	0.046	0.046	0.029	0.055	0.002	0.120	0.003	0.055	0.024	0.019	0.000	0.041	0.041	0.024
A5	0.008	0.000	0.000	0.000	0.005	0.000	0.029	0.005	0.013	0.008	0.000	0.017	0.005	0.000	0.008	0.029	0.000	0.008	0.000	0.008	0.008

Table 6 Relative weights of the attributes

	Attributes																				
	Cl	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21
Relative Weights	0.0357	0.0453	0.0536	0.0494	0.0424	0.0588	0.0535	0.0542	0.0438	0.0484	0.0368	0.0512	0.0467	0.0401	0.0451	0.0598	0.0543	0.0447	0.0391	0.0462	0.0508

Table 7 Fuzzy normalized decision matrix

Alternatives	Attributes																							
	Cl			C2			C3			C4			C5			C6			C7			C8		
Al	0.1000	0.3667	0.7000	0.0000	0.1000	0.5000	0.0000	0.0667	0.3000	0	0.3	0.7	0.1000	0.4333	0.7000	0.0000	0.1667	0.5000	0.0000	0.1667	0.5000	0.0000	0.0667	0.3000
A2	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000	0.5000	0.8333	1.0000	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000
A3	0.3000	0.5000	0.7000	0.1000	0.5667	0.9000	0.1000	0.4333	0.7000	0.3000	0.5667	0.9000	0.1000	0.3000	0.5000	0.1000	0.3000	0.5000	0.3000	0.5000	0.7000	0.1000	0.3667	0.7000

A4	0.0000	0.5667	1.0000	0.1000	0.5667	0.9000	0.0000	0.1667	0.7000	0.7000	0.9000	1.0000	0.0000	0.4333	1.0000	0.0000	0.1000	0.5000	0.0000	0.2667	0.7000	0.1000	0.4333	0.7000
AS	0.0000	0.5667	1.0000	0.3000	0.6333	0.9000	0.3000	0.6333	0.3000	0.5667	0.9000	1.0000	0.3000	0.6333	1.0000	0.3000	0.6333	0.9000	0.5000	0.7667	1.0000	0.3000	0.6333	0.3000

Table 7 Fuzzy Normalized decision matrix (Contd..)

Alternatives	Attributes																							
	C9			C10			C11			C12			C13			C14			C15			C16		
Al	0.1000	0.3000	0.5000	0.0000	0.2333	0.5000	0.0000	0.2333	0.7000	0.0000	0.1000	0.3000	0.0000	0.1667	0.5000	0.1000	0.3000	0.5000	0.0000	0.2333	0.5000	0.0000	0.0333	0.3000
A2	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000	0.5000	0.8333	1.0000	0.7000	0.9000	1.0000	0.5000	0.8333	1.0000	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000
A3	0.1000	0.3667	0.7000	0.1000	0.4333	0.7000	0.3000	0.6333	0.9000	0.3000	0.5667	0.9000	0.1000	0.5667	0.9000	0.5000	0.7000	0.9000	0.3000	0.6333	0.9000	0.1000	0.4333	0.9000
A4	0.1000	0.4333	0.7000	0.5000	0.8333	1.0000	0.0000	0.3667	0.9000	0.0000	0.5667	1.0000	0.0000	0.1667	0.7000	0.1000	0.5667	1.0000	0.0000	0.3667	0.9000	0.3000	0.7667	1.0000
A5	0.5000	0.7000	0.7000	0.5000	0.7000	0.9000	0.3000	0.6333	0.9000	0.3000	0.7667	1.0000	0.3000	0.7667	1.0000	0.3000	0.5667	0.9000	0.5000	0.7000	0.9000	0.5000	0.7667	1.0000

Table 7 Fuzzy Normalized decision matrix (Contd..)

Alternatives	Attributes														
	C17			C18			C19			C20			C21		
Al	0.0000	0.0667	0.3000	0.0000	0.1667	0.5000	0.0000	0.1000	0.3000	0.0000	0.1667	0.5000	0.0000	0.1000	0.5000
A2	0.7000	0.9000	1.0000	0.7000	0.9000	1.0000	0.5000	0.8333	1.0000	0.7000	0.9000	1.0000	0.5000	0.8333	1.0000
A3	0.3000	0.5000	0.7000	0.1000	0.5667	1.0000	0.3000	0.5667	0.9000	0.5000	0.7000	0.9000	0.5000	0.7000	0.9000
A4	0.5000	0.7000	0.9000	0.3000	0.6333	0.9000	0.0000	0.4000	0.9000	0.0000	0.4000	0.9000	0.3000	0.7667	1.0000
A5	0.3000	0.6333	0.9000	0.5000	0.7000	0.3000	0.6333	0.9000	0.5000	0.5000	0.7000	0.9000	0.5000	0.7667	1.0000

Table 8 Separation measures from positive ideal solution

Alternatives	Attributes																				
	Cl	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21
Al	0.0727	0.0707	0.0766	0.0600	0.0766	0.0712	0.0464	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A2	0.0273	0.0805	0.0402	0.0074	0.0086	0.0077	0.0061	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A3	0.0844	0.1330	0.0407	0.0764	0.0348	0.0260	0.0272	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A4	0.0002	0.0169	0.0090	0.0103	0.0172	0.0043	0.0061	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 9 Separation measures from negative ideal solution

Alternatives	Attributes																				
	Cl	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21
Al	0.05	0.00	0.00	0.00	0.15	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00
A2	0.53	0.67	0.66	0.55	0.60	0.67	0.65	0.74	0.56	0.62	0.48	0.73	0.56	0.56	0.62	0.75	0.74	0.71	0.65	0.65	0.58
A3	0.18	0.35	0.31	0.25	0.05	0.12	0.28	0.29	0.12	0.17	0.31	0.47	0.33	0.40	0.36	0.42	0.38	0.46	0.47	0.48	0.50
A4	0.20	0.35	0.23	0.55	0.29	0.00	0.12	0.31	0.13	0.53	0.13	0.48	0.11	0.32	0.24	0.61	0.58	0.47	0.38	0.26	0.51
A5	0.20	0.42	0.37	0.50	0.38	0.42	0.53	0.37	0.34	0.45	0.31	0.58	0.48	0.30	0.45	0.65	0.50	0.42	0.60	0.48	0.56

Table 10 Ranking of alternatives

Alternatives	GRG from PIS	GRG from NIS	CC	Rank by GRA
A1	0.7403	0.9852	0.4290	5
A2	0.6001	0.3434	0.6360	1
A3	0.4618	0.5376	0.4621	4
A4	0.4840	0.5473	0.4693	3
A5	0.4661	0.4357	0.5169	2

Table 11 Fuzzy Absolute difference of the compared series and the referential series

Alternatives	C1			C2			C3			C4			C5			C6			C7			C8		
A1	0.9000	0.6333	0.3000	1.0000	0.9000	0.5000	1.0000	0.9333	0.7000	1.0000	0.7000	0.3000	0.9000	0.5667	0.3000	1.0000	0.8333	0.5000	1.0000	0.8333	0.5000	1.0000	0.9333	0.7000
A2	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000	0.5000	0.1667	0.0000	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000
A3	0.7000	0.5000	0.3000	0.9000	0.4333	0.1000	0.9000	0.5667	0.3000	0.7000	0.4333	0.1000	0.9000	0.7000	0.5000	0.9000	0.7000	0.5000	0.7000	0.5000	0.3000	0.9000	0.6333	0.3000
A4	1.0000	0.4333	0.0000	0.9000	0.4333	0.1000	1.0000	0.8333	0.3000	0.3000	0.1000	0.0000	1.0000	0.5667	0.0000	1.0000	0.9000	0.5000	1.0000	0.7333	0.3000	0.9000	0.5667	0.3000
A5	1.0000	0.4333	0.0000	0.7000	0.3667	0.1000	0.7000	0.3667	0.7000	0.4333	0.1000	0.0000	0.7000	0.3667	0.0000	0.7000	0.3667	0.1000	0.5000	0.2333	0.0000	0.7000	0.3667	0.7000

Table 11 Fuzzy Absolute difference of the compared series and the referential series (Contd..)

Alternatives	C9			C10			C11			C12			C13			C14			C15		
A1	0.9000	0.7000	0.5000	1.0000	0.7667	0.5000	1.0000	0.7667	0.3000	1.0000	0.9000	0.7000	1.0000	0.8333	0.5000	0.9000	0.7000	0.5000	1.0000	0.7667	0.5000
A2	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000	0.5000	0.1667	0.0000	0.3000	0.1000	0.0000	0.5000	0.1667	0.0000	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000
A3	0.9000	0.6333	0.3000	0.9000	0.5667	0.3000	0.7000	0.3667	0.1000	0.7000	0.4333	0.1000	0.9000	0.4333	0.1000	0.5000	0.3000	0.1000	0.7000	0.3667	0.1000
A4	0.9000	0.5667	0.3000	0.5000	0.1667	0.0000	1.0000	0.6333	0.1000	1.0000	0.4333	0.0000	1.0000	0.8333	0.3000	0.9000	0.4333	0.0000	1.0000	0.6333	0.1000
A5	0.5000	0.3000	0.3000	0.5000	0.3000	0.1000	0.7000	0.3667	0.1000	0.7000	0.2333	0.0000	0.7000	0.2333	0.0000	0.7000	0.4333	0.1000	0.5000	0.3000	0.1000

Table 11 Fuzzy Absolute difference of the compared series and the referential series(Contd..)

Alternatives	C16			C17			C18			C19			C20			C21		
A1	1.0000	0.9667	0.7000	1.0000	0.9333	0.7000	1.0000	0.8333	0.5000	1.0000	0.9000	0.7000	1.0000	0.8333	0.5000	1.0000	0.9000	0.5000
A2	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000	0.3000	0.1000	0.0000	0.5000	0.1667	0.0000	0.3000	0.1000	0.0000	0.5000	0.1667	0.0000
A3	0.9000	0.5667	0.1000	0.7000	0.5000	0.3000	0.9000	0.4333	0.0000	0.7000	0.4333	0.1000	0.5000	0.3000	0.1000	0.5000	0.3000	0.1000
A4	0.7000	0.2333	0.0000	0.5000	0.3000	0.1000	0.7000	0.3667	0.1000	1.0000	0.6000	0.1000	1.0000	0.6000	0.1000	0.7000	0.2333	0.0000
A5	0.5000	0.2333	0.0000	0.7000	0.3667	0.1000	0.5000	0.3000	0.7000	0.3667	0.1000	0.5000	0.5000	0.3000	0.1000	0.5000	0.2333	0.0000

Table 12 Fuzzy grey relational coefficient

Alternatives	C1			C2			C3			C4			C5			C6			C7			C8		
A1	0.357	0.441	0.625	0.333	0.357	0.500	0.333	0.349	0.417	0.333	0.417	0.625	0.357	0.469	0.625	0.333	0.375	0.500	0.333	0.375	0.500	0.333	0.349	0.417
A2	0.625	0.833	1.000	0.625	0.833	1.000	0.500	0.750	1.000	0.625	0.833	1.000	0.625	0.833	1.000	0.625	0.833	1.000	0.625	0.833	1.000	0.625	0.833	1.000
A3	0.417	0.500	0.625	0.357	0.536	0.833	0.357	0.469	0.625	0.417	0.536	0.833	0.357	0.417	0.500	0.357	0.417	0.500	0.417	0.500	0.625	0.357	0.441	0.625
A4	0.333	0.536	1.000	0.357	0.536	0.833	0.333	0.375	0.625	0.625	0.833	1.000	0.333	0.469	1.000	0.333	0.357	0.500	0.333	0.405	0.625	0.357	0.469	0.625
A5	0.333	0.536	1.000	0.417	0.577	0.833	0.417	0.577	0.417	0.536	0.833	1.000	0.417	0.577	1.000	0.417	0.577	0.833	0.500	0.682	1.000	0.417	0.577	0.417

Table 12 Fuzzy grey relational coefficient (contd..)

Alternatives	C9			C10			C11			C12			C13			C14			C15			C16		
A1	0.357	0.417	0.500	0.333	0.395	0.500	0.333	0.395	0.625	0.333	0.357	0.417	0.333	0.375	0.500	0.357	0.417	0.500	0.333	0.395	0.500	0.333	0.341	0.417
A2	0.625	0.833	1.000	0.625	0.833	1.000	0.500	0.750	1.000	0.625	0.833	1.000	0.500	0.750	1.000	0.625	0.833	1.000	0.625	0.833	1.000	0.625	0.833	1.000
A3	0.357	0.441	0.625	0.357	0.469	0.625	0.417	0.577	0.833	0.417	0.536	0.833	0.357	0.536	0.833	0.500	0.625	0.833	0.417	0.577	0.833	0.357	0.469	0.833
A4	0.357	0.469	0.625	0.500	0.750	1.000	0.333	0.441	0.833	0.333	0.536	1.000	0.333	0.375	0.625	0.357	0.536	1.000	0.333	0.441	0.833	0.417	0.682	1.000
A5	0.500	0.625	0.625	0.500	0.625	0.833	0.417	0.577	0.833	0.417	0.682	1.000	0.417	0.682	1.000	0.417	0.536	0.833	0.500	0.625	0.833	0.500	0.682	1.000

Table 12 Fuzzy grey relational coefficient (Contd..)

Alternatives	C17			C18			C19			C20			C21		
A1	0.333	0.349	0.417	0.333	0.375	0.500	0.333	0.357	0.417	0.333	0.375	0.500	0.333	0.357	0.500
A2	0.625	0.833	1.000	0.625	0.833	1.000	0.500	0.750	1.000	0.625	0.833	1.000	0.500	0.750	1.000
A3	0.417	0.500	0.625	0.357	0.536	1.000	0.417	0.536	0.833	0.500	0.625	0.833	0.500	0.625	0.833
A4	0.500	0.625	0.833	0.417	0.577	0.833	0.333	0.455	0.833	0.333	0.455	0.833	0.417	0.682	1.000
A5	0.417	0.577	0.833	0.500	0.625	0.417	0.577	0.833	0.500	0.500	0.625	0.833	0.500	0.682	1.000

Table 13 Ranking of alternatives

Alternatives	Γ	Γ'	β	Rank
A1	0.5608	1.0000	0.1906	5
A2	1.0000	1.4392	0.8094	1
A3	0.6958	1.1350	0.3808	4
A4	0.7152	1.1544	0.4081	3
A5	0.8167	1.2559	0.5511	2

Table 14 Comparison of rankings by GRA and hybrid GRA methods

Alternatives	Ranking	
	GRA	Hybrid GRA-DEA
A1	5	5
A2	1	1
A3	4	4
A4	3	3
A5	2	2

6. Conclusion

In the present work a novel approach for performance evaluation and ranking of steel manufacturing organization through multi-attribute group decision making approaches are developed. In the proposed approaches, DEA, GRAand Integrated GRA-DEA decision making problems, fuzzy decision matrix with triangular fuzzy numbers are used to analyze and rank the performance of steel manufacturing organizations. The triangular fuzzy numbers are arrived from the linguistic expressions specified by group of decision makers.

The decision makers give linguistic evaluations of the attributes and rating of the alternatives on the basis of these attributes.The decision makers only roughly describe these values because of the uncertainty and vagueness of the information based on DMs preferences. Based on the preferences relative weights of the attributes obtained through objective method are considered in the study. In the study, triangular fuzzy numbersisthe best tool for solving decision-making problems with linguistic assessments. The use of triangular fuzzy numbers will give an adequate conversion of linguistic terms used by the decision makers into a multi-attribute group decision making problem.In general, in order to select the most appropriate model, the user (decision maker) has to set the criterion (objective function) that is most suitable for his/ her purpose (or to his / her opinion), and then decide on the approach to be used.DEA method identified all the steel manufacturing organizations as efficient, However, the rankings arrived by GRA and hybrid GRA-DEA approaches are similar though each ranking model has its own objective function.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest.

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