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A novel hybrid MCDM model for performance evaluation of research and technology organizations based on BSC approach

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A B S T R A C T

Balanced Scorecard (BSC) is a strategic evaluation tool using both financial and non-financial indicators to determine the business performance of organizations or companies. In this paper, a new integrated approach based on the Balanced Scorecard (BSC) and multi-criteria decision making (MCDM) methods are proposed to evaluate the performance of research centers of research and technology organization (RTO) in Iran. Decision-Making Trial and Evaluation Laboratory (DEMATEL) are employed to reflect the interdependencies among BSC perspectives. Then, Analytic Network Process (ANP) is utilized to weight the indices influencing the considered problem. In the next step, we apply four MCDM methods including Additive Ratio Assessment (ARAS), Complex Proportional Assessment (COPRAS), Multi-Objective Optimization by Ratio Analysis (MOORA), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for ranking of alternatives. Finally, the utility interval technique is applied to combine the ranking results of MCDM methods. Weighted utility intervals are computed by constructing a correlation matrix between the ranking methods. A real case is presented to show the efficacy of the proposed approach.

1. Introduction and literature review

Research centers and institutes are the project based locus of investigation for collaborative groups of researchers pushing the frontiers of knowledge forward. These centers need a proper evaluation and analysis system so as to make the process and results of the projects reach to a reasonable level and thus provide a sustainable development. Performance evaluation is defined as a significant measurement system by which an organization monitors its activities to assess whether the organization reaches the predefined objectives or the resources are allocated efficiently. As discussed by Rue, Byars, and Ibrahim (2012), performance measurement establishes a decision-making and communication process for improvement. Neely (1998) argue that a performance measurement system enables information decisions to be made and actions to be taken for quantifying the efficiency and effectiveness of past actions through a merger, separation, selection, analysis, interpretation and dissemination of appropri-ate data. In the field of performance measurement, mainly the strategic purposeshavebeenunderfocus.Thus,astrategic performance measurement method is required to achieve the goals in the short and long run strategic planning approach.

Various methods and techniques such as Data Envelopment Analysis (DEA), Balanced Scorecard (BSC), European Foundation of Quality Management (EFQM), Multi-Criteria Decision Making (MCDM) methods, Decision-Making Trial and Evaluation Laboratory (DEMATEL), Ratio Analysis, etc., aim at evaluating the activities carried out by a business for performance evaluation. Among these techniques, BSC is a strategic planning and management system that is used extensively to align business activities to the organizational strategies, improve internal and external communications, and monitor the organization. The Balanced Scorecard (BSC) system developed by Kaplan and Norton (1992, 1996) is one of these techniques integrating key measurement indices considering both financial and non-financial objectives. Four perspectives are presented that need to be balanced in performance measurement: financial perspective as a lagging indicator and customer, internal business process and learning and growth perspectives as leading indicators. These indicators can properly reflect the performance of a company and help evaluators make accurate decisions. Also, they can play a role as the criteria in MCDM techniques as they can be measured in both quantitative and qualitative approaches.

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Performance measurement using MCDM has attracted the attention of decision makers for a long time. Several multi-criteria decision making methods have been developed for performance measurement based on BSC indicators such as Analytic Hierarchy Process (AHP/Fuzzy AHP) (Farre-Danesh & Homayounfar, 2015; Keshavarz, Ftahikenari, Rohani, & Bagheri, 2014; Noori, 2015; Singh, Olugu, Musa, & Mahat, 2015; Singh & Sharma, 2014; Yadav & Sharma, 2015a), Analytic Network Process (ANP/Fuzzy ANP) (Lin, Chen, Tsai, & Tseng, 2014; Meena & Thakkar, 2014; Tseng, Lim, & Wong, 2015; Tjader, May, Shang, Vargas, & Gao, 2014),Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS/ Fuzzy TOPSIS) (Asli, Dalfard, & Poursalik, 2013; Mirfakhr-al-Dini, 2011; Nejatian & Zarei, 2013), DEMATEL (Farhangi, Meidanchi, & Ghanbari, 2015; Sorooshian, 2014; Shaik & Abdul-Kader, 2014), Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR/ Fuzzy VIKOR) (Sofiyabadi and Nasab, 2012), and Simple Additive Weighting (SAW) (Dodangeh, Dehafarin, & Nasehifar, 2012). Additive Ratio Assessment (ARAS), Complex Proportional Assessment (COPRAS), and Multi-Objective Basis of Ratio Analysis (MOORA) are new efficient MCDM methods that have been taken into consideration recently. A comprehensive comparison between the use of ARAS, COPRAS and other MCDM methods and their implementations are reviewed by Zavadskas and Turskis (2011). There are several works applying BSC to evaluate the performance, but there are few researchers using the recent methods such as ARAS, COPRAS, and MOORA considering BSC perspectives for performance evaluation. As a recent research in this regard, Rabbani, Zamani, Yazdani-Chamzini, and Zavadskas (2014). develop a new integrated approach based on the sustainable balanced scorecard, ANP, and COPRAS to evaluate the performance of oil producing companies. ANP is used to identify the interdependencies among the indicators. Then, COPRAS method is employed to prioritize the companies. The results indicate the effectiveness of the proposed model.

Also, several researchers develop the simultaneous use of these methods which are explained separately in the next paragraphs.

Leung, Lam, and Cao (2006). apply AHP and ANP to facilitate the implementation of the BSC. They show that the AHP and the ANP can be tailor-made for specific situations and can be used to overcome some of the traditional problems of BSC implementation, such as the dependency relationship between measures and the use of subjective versus objective measures. Applying AHP and ANP, Hamdan (2013) develops a performance evaluation model for Accounting Information Systems (AIS) in Jordanian business organizations, including commercial banks.

Yadav and Sharma (2015b) develop an integrated approach based on data envelopment analysis and AHP to evaluate supplier performance in the automobile industry. Chang (2015) integrates ANP and TOPSIS in a projects selection model for nonprofit TV stations. ANP method is used to obtain the weights of criteria and TOPSIS method is used to rank the alternatives. Jalaliyoon, Bakar, and Taherdoost (2014) propose a methodology using AHP and TOPSIS to implement balanced scorecard for operational appraisal of industrial groups. Tavana, Khalili-Damghani, and Rahmatian (2014) propose a hybrid fuzzy MCDM by DEMATEL and ANP for measuring the performance of publicly held companies in the pharmaceutical industry.

Hashemkhani Zolfani and Safaei Ghadikolaei (2012) use DEMATEL and ANP to identify relevant indices in each BSC perspectives to decrease the risk along with a short-term planning in private universities. They believe that the results of DEMATEL are of great importance. A fuzzy AHP is employed to determine the importance of each aspect of BSC by Ardekani, Morovati Sharifabadi, Jalaly, and Eghbali Zarch (2013). They suggest the application of Fuzzy VIKOR method to rank the ceramic and tile companies according to the BSC indices.

Azar, Olfat, Khosravani, and Jalali (2011) develop four evaluation models using VIKOR, TOPSIS and factor analysis to illustrate the cost reduction of each model for ranking suppliers. Three MCDM methods are applied to evaluate private universities by Wu, Lin, and Chang (2011). DEMATEL is used for evaluating cause and effect relations between perspectives of BSC and ANP is applied to identify significant criteria together with weights. They finally adopt VIKOR for comparing and ranking the universities. Yalcin, Bayrakdaroglu, and Kahraman (2012) propose a new financial performance evaluation approach to rank the manufacturing companies in a Turkish industry. Fuzzy AHP is used to determine the weights of the criteria. TOPSIS and VIKOR are then used to rank the companies according to their manufacturing sector. They reach the same ranking by these methods. Keramati and Shapouri (2015) present an integrated framework to measure the performance of Customer Relationship Management (CRM) system for Iranian Internet Service Provider (ISP) firms. DEMATEL is used to determine the interrelated relationships among criteria and to find influential factors. Criteria weights are then obtained by ANP. They finally adopt TOPSIS to analyze the CRM performance of ISP firms and conclude that some indicators paly an essential role in succeeding of CRM. Three MCDM methods, TOPSIS, VIKOR, and ELECTRE, are adopted to rank the banking performance by Shaverdi, Akbari, and Tafti (2011). Fuzzy AHP calculate the relative weights of each index to tolerate vagueness and ambiguity of information. The results show the customer as a significant BSC perspective. Table 1 reviews nearly all the recent studies in the field of performance measurement using MCDM techniques by BSC approach.

Finding the appropriate MCDM methods is very significant in performance evaluation. The use of a single prioritization method cannot ensure the best result; besides, such a result would not be robust (Akhavan, Barak, Maghsoudlou, & Antuchevičienė, 2015). Therefore, applying the combination of different MCDM methods has been proposed by several researchers as a more efficient technique to enhance the precision of the final decision. When the difference between the alternatives are inherently close together or when the number of alternatives increases, a robust aggregation method necessitates making reliable decisions (Jahan, Ismail, Shuib, Norfazidah, & Edwards, 2011; Hwang & Lin, 2012; Pomerol & Barba-Romero, 2012). Although the averaging function, as a basic aggregation strategy, is usually used to combine individual rankings by various MCDM methods, this process comprises no guarantee to obtain optimum results when there are great differences between the ranking values of alternatives (Jahan et al., 2011). The most prevalent aggregation methods are Borda and Copeland rules (Pomerol & Barba-Romero, 2012) for aggregation of different MCDM methods. The Borda selects the alternatives with the highest value. In Copeland's method alternatives are ordered by the number of pairwise victories, minus the number of pairwise defeats. Due to deficiencies exists in these two rules (Favardin, Lepelley, & Serais, 2002), there is a need for a systematic and logical scientific procedure to help decision- makers to achieve the optimum ranking of alternatives.

Therefore, a novel hybrid approach based on BSC and using the utility interval aggregation method is proposed in this study to evaluate the research centers of Research and Technology Organization (RTO) in which the evaluation indices are extracted based on project-based organizations. Furthermore, a weighted utility interval mechanism is used by considering the correlation matrix of the MCDM methods as a new approach.

In this study, a project based RTO in Iran is selected as a case for the performance evaluation. The provided case study results in further insights for research and practical applications.

The organization of the paper is as follows: The paper begins with the literature survey of performance evaluation based BSC

Table 1
A review of BSC studies based on MCDM methods.

Method	References
ANP & Fuzzy ANP (Recent two years)	Bhattacharya et al. (2014), Tjader et al. (2014), Boj et al. (2014), Dehnavi et al. (2014), Wang (2014), Lin et al. (2014), Cao and Jianxin (2014), Isfahani et al. (2014), Toosi and Tabari (2014), Meena and Thakkar (2014), Domanović et al. (2014), Tseng et al. (2015)
AHP & Fuzzy AHP (Recent two years)	Sorayaei et al. (2014), ElQuliti et al. (2014), Asl (2014), Kamfiroozi & Naeini (2014), Bansia et al. (2014), Quezada & López-Ospina (2014), De Felice and Petrillo (2014), Gramani (2014), Noori (2014), Safdari et al. (2014), Nippak et al. (2014), Akyuz et al. (2015), Haddadi and Yaghoobi (2014), Kader Ahmed (2014), Iqbal (2014), Penić and Dobrović (2014), Kao et al. (2014), Kashi and Franek (2014), Keshavarz et al. (2014), Farre-Danesh and Homayounfar (2015), Singh et al. (2015), Noori (2015)
TOPSIS	Mirfakhr-al-Dini (2011), Manian et al. (2011), Afacant & Tolga (2012), Shojaee and Fallah (2012), Shivakumar et al. (2013), Asli et al. (2013), Nejatian and Zarei (2013)
ANP, DEMATEL & VIKOR	Manousakas et al. (1998), Tsai et al. (2010a, 2010b), Wu et al. (2011), Chen (2011), Hashemkhani Zolfani and Safaei Ghadikolaei (2012)
ANP &DEMATEL	Tsai et al. (2009), Tseng (2010), Chen et al. (2011), Su et al. (2011), Araghia and Yousefie (2012), Alvandi et al. (2012), Jafari-Eskandari et al. (2013), Tavana et al. (2014)
TOPSIS, VIKOR& AHP	Wu et al. (2009), Yalcin et al. (2012)
AHP & VIKOR	Ardekani et al. (2013)
ANP & COPRAS	Rabbani et al. (2014)
AHP & TOPSIS	Montazer & Ebrahimian (2011), Fakharian et al. (2014), Jalaliyoon et al. (2014), Taroghi and Yaqubi (2015), Alidade and Ghasemi (2015)
DEMATEL	Heydariyeh et al. (2012), Wu (2012), Nasab (2012), Shafiee et al. (2014) Sorooshian (2014), Shaik and Abdul-Kader (2014), Farhangi et al. (2015)
DEMATEL, ANP & AHP	Mozaffari et al. (2012), Hashemkhani Zolfani and Safaei Ghadikolaei (2012)
AHP & ANP	Leung et al. (2006), Hamdan (2013), Medel-González et al. (2013)
ANP, DEMATEL & TOPSIS	Keramati and Shapouri (2015)
VIKORE	Sofiyabadi and Nasab (2012)
SAW & TOPSIS	Ardabili (2011)
TOPSIS & VIKOR	Azar et al. (2011)
SAW, VIKOR, & TOPSIS	Momeni et al. (2011)
SAW	Dodangeh et al. (2012)
ANP &TOPSIS	Beig et al. (2012), Chang (2013), Chang (2015)
TOPSIS, VIKOR &ELECTRE	Shaverdi et al. (2011)

applying MCDM methods. Section 2 introduces the steps in the proposed model while Section 3 elucidates the case under study and presents the detailed application of the proposed model concerning a case study. Finally, in Section 4 we draw our conclusions and offer recommendations for future research. A brief review of methodologies is also described in Appendix A.

2. Proposed approach

Based on literature review a hybrid approach, shown in Fig. 1, is proposed to establish a performance evaluation model for RTOs. The process is carried out in five steps after forming an expert committee to get their opinion on perspectives and indices pReferences

(1) Performance evaluation indices of research centers of RTO are collected;
(2) The DEMATEL method is applied to determine interrelationships among four BSC perspectives;
(3) ANP is used to calculate the weights of BSC perspectives and indices;
(4) Performance for each of the potential RTO centers is evaluated using ARAS, COPRAS, MOORA and TOPSIS methods based on evaluation indices to rank the preference order among the cases.
(5) The utility interval is employed to compound the results of the methods in step (4) to get the final results.

All of the evaluation methods in steps (2), (3) and (4) are explained in Appendix A.

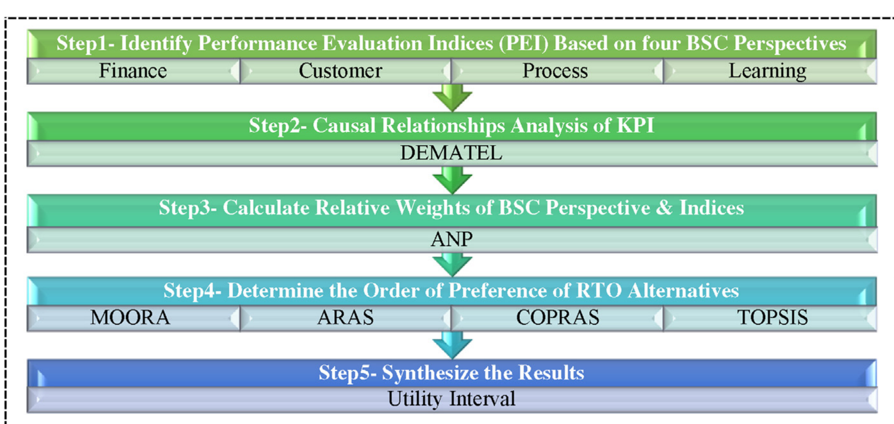

Fig. 1. Proposed evaluation model of RTO centers.

Table 2
Background information of the committee members.

Category	No.	Category	No.
Working Level		Years of working experiences	
Top managers	4	≤5 years	1
Project managers	4	>5 years and ≤10 years	2
Researcher	2	>10 years and ≤15 years	3
Education level		>15 years and ≤20 years	2
Bachelor	0	>20 years	2
Master	3		
Ph.D.	7		

3. Case study

In this section, an empirical study is presented to illustrate the application of the proposed model for evaluating research centers of RTO. The problem description, the background information of experts consulted, the influencing indices, as well as the results of all the processes of analysis and evaluation, are elaborated as follows.

3.1. Problem description

Research Institute of Petroleum Industry (RIPI) established as an RTO with 12 centers in Iran. Its primary aim is carrying out research on the application of petroleum materials. Production of valuable products such as technical knowledge, patents, transfer & indigenization of refinery technologies and advisory services for optimizing and solving the industries problems are the main activities which are project based.

Due to the competitive environment among the 12 research centers, performance evaluation appears to be significant. Thus, RIPI is planned to be evaluated periodically for strategic reasons such as identifying strengths and weaknesses, resource assignment and planning improvement. Consequently, the proposed methodology (section 2-Fig. 1) is employed to prioritize the 12 centers.

3.2. Background information of experts

For identifying the indices and determining the related preferences, we formed an expert committee with ten members including top managers, project managers, and researchers. The background information of experts of this research is presented in Table 2.

Most of the committee members are more than five years experienced in managerial level with graduate education.

3.3. Determining the performance evaluation indices

Performance evaluation indices of research organizations are collected from the BSC literature (Bhagwat & Sharma, 2007; Hsieh, 2005; Kaplan & Norton, 1996; Kaplan & Tempest, 1998; Project Management Institute, 2013; Sharma & Bhagwat, 2007; Tsai, Chou, & Hsu, 2009; Wu et al., 2011) and by the professional experts as a basic evaluation step of this research.

31 performance indices based BSC perspectives are identified. The indices are scored, scaled 1–10, by committee members. The average scores of each index are shown in Appendix B. According to the experts' opinions, the most relevant indices with average scores over 8.5 are chosen for performance evaluation (17 from 31 indices). Table 3 illustrates the four BSC perspectives and the summarized indices.

3.4. Cause and effects analysis of four BSC perspectives with DEMATEL

The DEMATEL method is an effective procedure for analyzing the structure and establishing relationships between components or alternatives. It is based on digraphs, which can separate involved factors into cause group and effect group and convert the relationship between the causes and effects of criteria into an explicit structure. According to the explanation of DEMATEL in Appendix A.1, the following five steps are pursued to derive mutual causality of four BSC perspectives.

Step 1: Find the average matrix.

Table 3
BSC perspectives and related indices.

Perspectives/Indices	Definition
01-Financial	
011-Net profit rate	Ratio of net profit sales to sales amount
012-Contract value	Total amount of contracts values
013-Cost performance index (CPI) Cost Performance Index = (Earned Value)/(Actual Cost)	The value of the work completed compared to the actual cost spent on the project
014-Unexpected cost (UC) Index Unexpected cost Index = Actual UC/predicted UC	The predefined percentage of total budget considered for uncontrollable evidence resulting from force major, political and economic effects
02-Customer (C)	
021-Customer complaints	A number of complaints to products and services directly addressed to a company or service providers
022-Long-term customer retention index	Repeat customer rate (RCR), (RCR = Customers that have purchased more than once/Total Customers)
023-Quality performance index (QPI)	The quality of finalized project from the customer view point to ensure that the project requirements are met and validated.
024-Expanding and development of customers	A number of new customers to build a continuous feedback loop with current customers
03-Internal process (P)	
031-After-sales service offer	Process improvement value by customers' feedback from receiving the services after project accomplishment.
032-Setting up annual objectives	If core programs and objectives are identified in the evaluation period.
033-Core business process	Core business processes improvement value after monitoring their performance in the evaluation period
034-Schedule Performance Index (SPI)	Time evaluation of projects
035-Risk management	Number of identified risks to number of managed risks
04-Learning and growth (L)	
041-Employee turnover	Number or percentage of workers who leave an organization and are replaced by new employees
042-Lessons learned	An average number of documented knowledge retrieved form the projects in the evaluation period
043-Education metrics	Total number of training hours divided by total number of employees
044- Scientific score	A number of scientific works and patents

Table 4
Average relation matrix.

	Financial	Customer	Internal process	Learning & Growth	Sum
Financial	0	1.657	1.229	2.343	5.229
Customer	1.543	0	1.143	1.686	4.372
Internal process	1.486	1.371	0	1.571	4.428
Learning & Growth	2.286	2.080	1.543	0	5.915
Sum	5.315	5.114	3.915	5.6	5.915

Table 5
Direct relation matrix.

	Financial	Customer	Internal process	Learning & Growth
Financial	0	0.2801	0.2078	0.3961
Customer	0.2609	0	0.1932	0.285
Internal process	0.2512	0.2318	0	0.2656
Learning & Growth	0.3865	0.3527	0.2609	0

Table 6
Indirect relation matrix.

	Financial	Customer	Internal process	Learning & Growth
Financial	1.3893	1.2871	1.0415	1.3289
Customer	1.1408	1.1602	0.8964	1.1753
Internal process	1.1474	1.1195	0.9304	1.1863
Learning & Growth	1.3961	1.3674	1.1098	1.5604

Ten experts score the relation matrix of four perspectives from 0 to 4 (No influence (0), Very high influence (4)) to represent different influential extents. Then, the average matrix is calculated by Eq. (A1) provided in Table 4. For instance, the value 2.08 depicts the effect of “learning and growth” on “customer” indicating a medium influence value.

Steps 2: Calculate the direct relation matrix.

The maximum value among the sum of rows and columns is 5.915 illustrated in Table 4. Based on Eq. (A2) s equals 1/5.915 and the direct influence matrix is computed by Eq. (A3) for which the results are presented in Table 5.

Step 3, 4: Calculate the indirect and total relation matrix.

Sequentially, the indirect relation matrix (**ID**), Table 6, and the total relation matrix (**T**), Table 7, are derived utilizing Eqs. (A4) and (A5) respectively.

To find the degree of relation among perspectives Eqs. (A7) and (A8) are used. The sum of rows (i) and columns (j) in total relation matrix (**T**) represent d_i and r_j respectively shown in Table 8. The values of d_i+ r_i and d_i- r_i are displayed in Table 8 if $d_i - r_i$ is negative, the perspective belongs to the affected group. Otherwise, it belongs to the cause group.

Step 5, 6: Obtain the influence-relations map.

Table 7
Total relation matrix.

	Financial	Customer	Internal process	Learning & Growth
Financial	1.3893	1.5672	1.2493	1.725
Customer	1.4016	1.1602	1.0896	1.4603
Internal process	1.3986	1.3513	0.9304	1.4519
Learning & Growth	1.7826	1.72	1.3707	1.5604

Table 8
Degree of total relation of the perspectives.

	d	r	$d+r$	$d-r$	Group
Financial	5.9308	5.9721	11.903	−0.0413	‘Affected’
Customer	5.1118	5.7987	10.9106	−0.6869	‘Affected’
Internal process	5.1322	4.64	9.7722	0.4922	‘Cause’
Learning & Growth	6.4337	6.1976	12.6313	0.2361	‘Cause’

Table 9
Net relation matrix.

	Financial	Customer	Internal process	Learning & Growth
Financial	0			
Customer	−0.1656	0		
Internal process	0.1493	0.2616	0	
Learning & Growth	0.0576	0.2597	−0.0812	0

To obtain an appropriate relationship map, $(d+r)$ and $(d-r)$ are considered as X-axis and Y-axis respectively. The net relation matrix (Table 9) is developed to find out the influential relation values between evaluation perspectives by setting a threshold of 0.05 by experts' opinions. Subsequently, the causal diagram is drawn as presented in Fig. 2 in which “Financial” perspective is affected by “Learning and growth”, “customer” and “internal process” perspectives. Therefore, the growth of financial perspective depends on the growth of other three perspectives.

3.5. ANP analysis to identify the weight of indices

The ANP method, proposed by Saaty (1996), remove the restriction of hierarchical structure and independence among elements. The hierarchies are replaced by networks in which the relationships between levels are not easily represented as higher or lower, dominant or subordinate.

In this step, ANP is developed based on the result of the previous section in which the causal relationships of four BSC

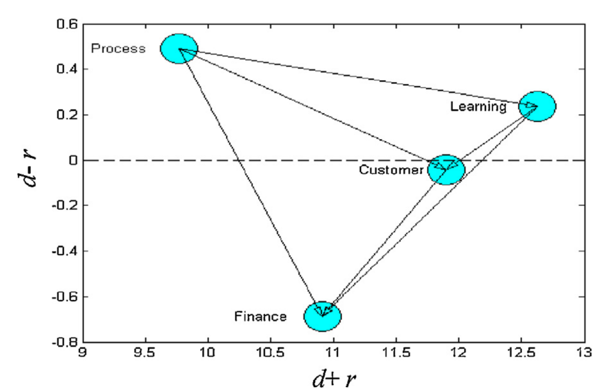

Fig. 2. Causal influence relation map.

Table 10
limiting supermatrix.

	021	022	023	024	011	012	013	014	031	032	033	034	035	041	042	043	044
021	0.05	0.05	0.05	0.05	0.00	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
022	0.03	0.03	0.03	0.03	0.00	0.03	0.00	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
023	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
024	0.17	0.17	0.17	0.17	0.00	0.17	0.00	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
011	0.15	0.15	0.15	0.15	0.00	0.15	0.00	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
012	0.03	0.03	0.03	0.03	0.00	0.03	0.00	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
013	0.05	0.05	0.05	0.05	0.00	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
014	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
031	0.05	0.05	0.05	0.05	0.00	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
032	0.11	0.11	0.11	0.11	0.00	0.11	0.00	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
033	0.02	0.02	0.02	0.02	0.00	0.02	0.00	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
034	0.02	0.02	0.02	0.02	0.00	0.02	0.00	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
035	0.08	0.08	0.08	0.08	0.00	0.08	0.00	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
041	0.05	0.05	0.05	0.05	0.00	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
042	0.08	0.08	0.08	0.08	0.00	0.08	0.00	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
043	0.05	0.05	0.05	0.05	0.00	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
044	0.05	0.05	0.05	0.05	0.00	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

perspectives are established. The experts' opinions are extracted from ANP questionnaires and entered to "Super Decision" software to get the relative weights of performance indices of each perspective. The process analysis of ANP as explained in Appendix A.2 is follows:

According to the causal relation map of BSC perspectives (Fig. 2) and the related indices provided in Table 3, a pairwise comparison questionnaire matrix is developed to get the experts' opinions. The geometric means of collected data are entered into the "Super Decision" software to make the unweighted, weighted and limiting supermatrices (Table 10). Table 11 presents the weights of BSC perspectives and performance indices.

Table 11
Weights of perspectives and indices.

Perspectives/Indic	Weights
01-Financial	**0.46**
011-Net profit rate	0.45
012-Contract value	0.20
013-Cost performance index (CPI)	0.17
014-Unexpected cost (UC) Index	0.17
02-Customer (C)	**0.26**
021-Customer complaints	0.51
022-Long-term customer retention index	0.11
023-Quality performance index (QPI)	0.20
024-Expanding and development of customers	0.17
03-Internal process (P)	**0.10**
031-After-sales service	0.11
032-Setting up annual objectives	0.33
033-Core business process	0.10
034-Schedule Performance Index (SPI)	0.16
035-Risk management	0.31
04-Learning and growth (L)	**0.18**
041-Employee turnover	0.57
042-Lessons learned	0.20
043-Education metrics	0.11
044-Scientific score	0.12

3.6. Determine the order of preference of RTO alternatives

Based on the nature of MCDM combination methods explained in the introduction, it is preferred to aggregate the same type MCDM methods on the basis of the input information.

Turskis and Zavadskas (2010) and Zavadskas and Turskis (2010) proposed different types of MCDM methods which can be used for complex problem solutions:

a Methods based on quantitative measurements, such as TOPSIS, SAW, MOORA, ARAS, COPRAS.
b Methods based on qualitative initial measurements such as AHP, ANP etc.
c Comparative preference methods based on pair-wise comparison of alternatives such as PROMETHEE and ELECTERE.
d Methods based on qualitative measurements not converted to quantitative variables such as verbal decision-making analysis.

Thus, we selected the first type methods (a) since the input information of performance measurement of RTOs is generally quantitative.

In this section, four ranking methods, MOORA, ARAS, COPRAS, and TOPSIS are used to rank the 12 research centers. The required information, as the inputs of these methods, for ranking the alternatives (research centers) is collected in Appendix C. The methods are developed and run by MATLAB R2014a.

3.6.1. MOORA method

Based on the existing definitions by Brauers, Zavadskas, Peldschus, and Turskis (2008) and Chakraborty (2011); MOORA is applied as a multi-objectives optimization method which starts with a matrix of responses of different alternatives on different objectives. The objectives (attributes) must be measurable and their outcomes can be measured for every decision alternative. Objective outcomes provide the basis of comparison of choices and consequently facilitate the selection of the best (satisfactory) choice. To define the objectives, a closer focus on the notion of attributes and objectives is required. Keeney and Raiffa (1993) present the example of the objective "reduce sulfur dioxide emissions" to be measured by the attribute "tons of sulfur dioxide emitted per year". Thus, an objective and a correspondent attribute always go together (Brauers & Zavadskas, 2006). In this study, the experts' opinions are solicited and synthesized for determining the indices of the most relevant and important attributes on each BSC

Table 12
Weights and attribute types of performance indices.

Indices	w	Attribute Type
011-Net profit rate	0.207	+1
012-Contract value	0.092	+1
013-Cost performance index (CPI)	0.0782	+1
014-Unexpected cost (UC) Index	0.0782	−1
021-Customer complaints	0.1326	−1
022-Long-term customer retention index	0.0286	+1
023-Quality performance index (QPI)	0.052	+1
024-Expanding and development of customers	0.0442	+1
031-After-sales service offer	0.011	+1
032-Setting up annual objectives	0.033	+1
033-Core business process	0.01	+1
034-Schedule Performance Index (SPI)	0.016	+1
035-Risk management	0.031	+1
041-Employee turnover	0.1026	−1
042-Lessons learned	0.036	+1
043-Education metrics	0.0198	+1
044-Scientific score	0.0216	+1

−1 = non-beneficial, +1 = beneficial indices.

perspective. Consequently, when the text mentions objective, the correspondent attribute/indices is also meant. Calculations of MOORA method are made following Appendix A.3. The weights of indices are extracted from ANP method acquired from Table 11. The separation of beneficial and non-beneficial indices (+1/−1) and the related weights are represented in Table 12. In this method, the optimization score (Y) is calculated, and finally, the rank of alternatives is obtained. As indicated in Table 13, research centers 1, 7 reached the maximum scores.

3.6.2. ARAS method

According to the ARAS method, a utility function value determining the complex relative efficiency of a feasible alternative is directly proportional to the relative effect of values and weights of the main criteria considered in a project (Zavadskas & Turskis, 2010). In this method, the value of optimality function (S) and the utility degree (K) are determined based on ARAS method explained in Appendix A.4 and the weights and type of indices indicated in Table 12. The first row of Table 14 consists the value optimality function (S), the next row is the utility degrees of alternatives (k), and the last row is the rank of the research centers. The most reasonable alternative according to calculation results is R1. It means that the best alternative is the first research center, and the worst alternative is the 11th research center. It can be stated that the alternative 1 is only 72% of optimal alternative performance level, and the performance of the worst alternative 11 is only 23%.

3.6.3. COPRAS method

The COPRAS method, introduced by Zavadskas and Kaklauskas (1996), is a compromising MCDM technique to find a solution on the positive and negative-ideal solutions. In the current case, based on Appendix A.5 and Table 12 the minimizing index value (R), a maximizing index value (P) and the relative significance value (Q)

Table 13
Ranking results of MOORA.

Research Center	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
Y	0.256	0.085	0.095	0.091	0.095	0.074	0.200	0.054	0.045	0.063	−0.026	0.062
Rank	1	6	4	5	3	7	2	10	11	8	12	9

Table 14
The optimality function and the degree of an alternative value resulting from the ARAS method.

Research Center	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
S	0.119	0.061	0.081	0.063	0.069	0.058	0.108	0.054	0.056	0.065	0.038	0.062
K	0.725	0.372	0.492	0.385	0.418	0.355	0.658	0.326	0.344	0.396	0.233	0.378
Rank	1	8	3	6	4	9	2	11	10	5	12	7

Table 15
Maximizing and minimizing indices, relative significance of alternatives and final ranking of COPRAS.

Research Center	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
R	0.111	0.046	0.085	0.055	0.066	0.046	0.085	0.046	0.039	0.042	0.026	0.040
P	0.023	0.019	0.052	0.024	0.032	0.021	0.018	0.027	0.024	0.021	0.034	0.019
Q	0.138	0.080	0.097	0.081	0.085	0.076	0.120	0.069	0.065	0.072	0.044	0.073
Rank	1	6	2	5	4	8	3	7	11	9	12	10

Table 16
Negative and positive ideal solutions, RC and the ranking of TOPSIS.

Research Center	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
S^-	0.026	0.006	0.008	0.007	0.008	0.006	0.014	0.005	0.005	0.006	0.004	0.006
S^+	0.004	0.019	0.016	0.015	0.011	0.018	0.006	0.017	0.022	0.021	0.029	0.019
RC	0.878	0.705	0.415	0.334	0.320	0.253	0.238	0.223	0.217	0.214	0.184	0.113
Rank	1	8	4	5	3	7	2	9	11	10	12	6

Table 17
The ranking results of four MCDM methods.

Method	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
MOORA	1	6	4	5	3	7	2	10	11	8	12	9
ARAS	1	8	3	6	4	9	2	11	10	5	12	7
COPRAS	1	6	2	5	4	8	3	7	11	9	12	10
TOPSIS	1	8	4	5	3	7	2	9	11	10	12	6

are computed, and the complete ranking of research centers is obtained (See Table 15). The alternative with the highest relative weights is considered as the best alternative. From Table 15, the first research center, R1, has the higher relative weight and hence the R11 has less performance score.

3.6.4. TOPSIS method

As discussed in Appendix A.6, the TOPSIS method is applied to the case under study. Calculations are made to form the negative and positive ideal solutions (S^{+}, S^{-}) and the relative closeness to the ideal alternatives (RC) to evaluate the performance of research centers. The results of the TOPSIS method are summarized in Table 16, indicating the ranking of research centers. According to the closeness coefficient (RC), the ranking of the alternatives can be determined. Obviously, Alternative R1 which has the highest priority weight is selected as the best center among RIPI centers.

3.7. Aggregation of MCDM method

If all alternatives ranking orders in different MCDM methods are quite the same, the decision-making process will be ended. Different MCDM methods regularly create different outcomes for selecting or ranking a set of alternative decisions involving multiple criteria (Jahan et al., 2011). Furthermore, if the number of alternative increases (Olson, Moshkovich, Schellenberger, & Mechitov, 1995), or if the alternatives have similar performance (Olson et al., 1995; Shanian & Savadogo, 2009), the ranking outcome of different MCDM techniques differ significantly which lead to inconsistency and thus the validity and reliability issues will be crucial (Hobbs, Chankong, Hamadeh, & Stakhiv, 1992). Considerable effort has been spent on the development of numerous MCDM models, but there is no comprehensive approach or no single multi-criteria analysis technique to be inherently better than the others (Hajkowicz & Collins, 2007).

In this article, each of four ranking methods (Table 17) provides different information on the degrees of preference while an accurate combination method is required to determine the final preferences. Thus, the utility interval aggregation method in multi-criteria decision-making is used to fill the gap and to enhance the reliability of the performance evaluation and thus the ranking results. Therefore, the proposed aggregation model is capable of assisting managers to make robust decisions in ranking research centers. Wang, Yang, and Xu (2005) provide a review of the aggregation methods. They show that utility interval method is preferred to other aggregation methods because it provides information on the degree of preference and is thus easier to be understood and accepted. In this research, the achieved rankings by four methods of MOORA, ARAS, COPRAS and TOPSIS are consolidated using utility interval.

A linear programming (LP) model is first constructed to estimate the interval for each alternative (research centers in this study). This model should be solved for each ranking method, $i = 1, \ldots, m$, by Eqs. (1)–(4).

$$\min/\max \qquad u_{i1} \tag{1}$$

Table 18
Utility interval estimates corresponding to the preference ranking of MCDM methods.

	Method	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
ε = 0	MOORA	[0.0833, 1]	[0, 0.1667]	[0, 0.25]	[0, 0.2]	[0, 0.3333]	[0, 0.1429]	[0, 0.5]	[0, 0.1]	[0, 0.0909]	[0, 0.125]	[0, 0.0833]	[0, 0.111]
	ARAS	[0.0833, 1]	[0, 0.125]	[0, 0.3333]	[0, 0.1667]	[0, 0.25]	[0, 0.1111]	[0, 0.5]	[0, 0.0909]	[0, 0.1]	[0, 0.2]	[0, 0.0833]	[0, 0.143]
	COPRAS	[0.0833, 1]	[0, 0.1667]	[0, 0.5]	[0, 0.2]	[0, 0.25]	[0, 0.125]	[0, 0.3333]	[0, 0.1429]	[0, 0.0909]	[0, 0.1111]	[0, 0.0833]	[0, 0.1]
	TOPSIS	[0.0833, 1]	[0, 0.125]	[0, 0.25]	[0, 0.2]	[0, 0.3333]	[0, 0.1429]	[0, 0.5]	[0, 0.1111]	[0, 0.0909]	[0, 0.1]	[0, 0.0833]	[0, 0.1667]
ε = 0.01	MOORA	[0.1383, 0.45]	[0.06, 0.1167]	[0.08, 0.165]	[0.07, 0.138]	[0.09, 0.2033]	[0.05, 0.0986]	[0.1, 0.27]	[0.02, 0.054]	[0.01, 0.0409]	[0.04, 0.0825]	[0, 0.0283]	[0.03, 0.06778]
	ARAS	[0.1383, 0.45]	[0.04, 0.0825]	[0.09, 0.2033]	[0.06, 0.1167]	[0.08, 0.165]	[0.03, 0.0678]	[0.1, 0.27]	[0.01, 0.0409]	[0.02, 0.054]	[0.07, 0.138]	[0, 0.0283]	[0.05, 0. 09857]
	COPRAS	[0.1383, 0.45]	[0.06, 0.1167]	[0.1, 0.27]	[0.07, 0.138]	[0.08, 0.165]	[0.04, 0.0825]	[0.09, 0.2033]	[0.05, 0.0986]	[0.01, 0.0409]	[0.03, 0.0678]	[0, 0.0283]	[0.02, 0. 054]
	TOPSIS	[0.1383, 0.45]	[0.04, 0.0825]	[0.08, 0.165]	[0.07, 0.138]	[0.09, 0.2033]	[0.05, 0.0986]	[0.1, 0.27]	[0.03, 0.0678]	[0.01, 0.0409]	[0.02, 0.054]	[0, 0.0283]	[0.06, 0. 1167]
ε = 0.015	MOORA	[0.1667, 0.1667]	[0.0909, 0.0909]	[0.1212, 0.1212]	[0.1061, 0.1061]	[0.1364, 0.1364]	[0.0758, 0.0758]	[0.1515, 0.1515]	[0.0303, 0.0303]	[0.0152, 0.0152]	[0.0606, 0.0606]	[0, 0]	[0.0455, 0. 0455]
	ARAS	[0.1667,0.1667]	[0.0606, 0.0606]	[0.1364, 0.1364]	[0.0909, 0.0909]	[0.1212, 0.1212]	[0.0455, 0.0455]	[0.1515, 0.1515]	[0.0152, 0.0152]	[0.0303, 0.0303]	[0.1061, 0.1061]	[0, 0]	[0.0758, 0. 0758]
	COPRAS	[0.1667, 0.1667]	[0.0909, 0.0909]	[0.1515,0.1515]	[0.1061, 0.1061]	[0.1212, 0.1212]	[0.0606, 0.0606]	[0.1364, 0.1364]	[0.0758, 0.0758]	[0.0152, 0.0152]	[0.0455, 0.0455]	[0, 0]	[0.0303, 0. 0303]
	TOPSIS	[0.1667, 0.1667]	[0.0606, 0.0606]	[0.1212, 0.1212]	[0.1061, 0.1061]	[0.1364, 0.1364]	[0.0758, 0.0758]	[0.1515, 0.1515]	[0.0455, 0.0455]	[0.0152, 0.0152]	[0.0303, 0.0303]	[0, 0]	[0.0909, 0. 0909]

Table 19
Correlation matrix and weights of methods.

Methods	COPRAS	MOORA	ARAS	TOPSIS
COPRAS	1	0.937	0.825	0.888
MOORA	0.937	1.000	0.909	0.937
ARAS	0.825	0.909	1	0.867
TOPSIS	0.888	0.937	0.867	1.000
SUM	3.65	3.783	3.601	3.692
Weight	0.25	0.26	0.24	0.25

$$s.t. \qquad u_{ij} - u_{i(j+1)} \geq \varepsilon_{j(j+1)} \qquad j = 1, 2, ..., n-1 \tag{2}$$

$$\sum_{j=1}^{n} u_{ij} = 1 \tag{3}$$

$$u_{ij} \geq 0 \qquad j = 1, 2, ..., n. \tag{4}$$

where u_{ij} is the utility of the j^{th} ranked alternative perceived by the i^{th} ranking method. Eq. (1), objective function, calculates the minimum and maximum interval numbers, $[u_{ij}^L, u_{ij}^U]$, for the first ranked alternative by each ranking method. To minimize Eq. (2) shows the preference of alternative j to alternative $j+1$ in the ith ranking method, where ε is a small positive number. The normalized utility vector is presented by Eq. (3).

In the current study, the number of alternatives (i) and the number of ranking methods (j) equal 12 and 5, respectively. To simplify the above LP model, $\varepsilon_{j(j+1)}$ is assumed to be equal to ε ($\varepsilon_{j(j+1)} = \varepsilon$). As given by Wang et al. (2005); ε is ranged as follow:

$$0 \leq \varepsilon \leq \varepsilon_{\max} = \frac{1}{n(n-1)/2} \tag{5}$$

In this case, $\varepsilon_{\max} = 1/66$, ($n = 12$). Therefore, three sets of evaluation are run for $\varepsilon = 0$, 0.01, 0.015. Table 18 provides all the utility estimates that are generated from the rankings indicated in Table 17 and LP model.

The aggregated utility (weighted average utility) of each alternative (research centers) can be calculated as follows:

$$u_j^L = \sum_{i=1}^{m} w_i u_{ij}^L, \qquad j = 1, ..., n. \tag{6}$$

Table 20
The weighted average utility interval for ε=0 and ε=0.01.

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
$\varepsilon = 0$	[0.08333, 1]	[0, 0.146]	[0, 0.3323]	[0, 0.1918]	[0, 0.2923]	[0, 0.1307]	[0, 0.4587]	[0, 0.1112]	[0, 0.09313]	[0, 0.1336]	[0, 0.08333]	[0, 0.13]
$\varepsilon = 0.01$	[0.1383, 0.45]	[0.05009, 0.09975]	[0.0874, 0.2004]	[0.06755, 0.1328]	[0.08508, 0.1845]	[0.04263, 0.08706]	[0.09752, 0.2535]	[0.0275, 0.0653]	[0.01245, 0.04411]	[0.03984, 0.08528]	[0, 0.02833]	[0.03993, 0.08415]
$\varepsilon = 0.015$	[0.1667, 0.1667]	[0.0759, 0.0759]	[0.1324, 0.1324]	[0.1024, 0.1024]	[0.1289, 0.1289]	[0.06459, 0.06459]	[0.1478, 0.1478]	[0.04166, 0.04166]	[0.01886, 0.01886]	[0.06037, 0.06037]	[0, 0]	[0.06051, 0.06051]

Table 21
The aggregated rankings corresponding to Table 20.

	Ranking
$\varepsilon = 0$	$R_1 \overset{0.7271}{\succ} R_7 \overset{0.5799}{\succ} R_3 \overset{0.5321}{\succ} R_5 \overset{0.6037}{\succ} R_4 \overset{0.5678}{\succ} R_2 \overset{0.5222}{\succ} R_{10} \overset{0.5056}{\succ} R_6 \overset{0.5012}{\succ} R_{12} \overset{0.5391}{\succ} R_8 \overset{0.5442}{\succ} R_9 \overset{0.5278}{\succ} R_{11}$
$\varepsilon = 0.01$	$R_1 \overset{0.7538}{\succ} R_7 \overset{0.6175}{\succ} R_3 \overset{0.543}{\succ} R_5 \overset{0.7102}{\succ} R_4 \overset{0.7198}{\succ} R_2 \overset{0.6071}{\succ} R_6 \overset{0.5254}{\succ} R_{10} \overset{0.5058}{\succ} R_{12} \overset{0.6907}{\succ} R_8 \overset{0.7609}{\succ} R_9 \overset{0.7352}{\succ} R_{11}$
$\varepsilon = 0.015$	$R_1 \overset{1}{\succ} R_7 \overset{1}{\succ} R_3 \overset{1}{\succ} R_5 \overset{1}{\succ} R_4 \overset{1}{\succ} R_2 \overset{1}{\succ} R_6 \overset{1}{\succ} R_{12} \overset{1}{\succ} R_{10} \overset{1}{\succ} R_8 \overset{1}{\succ} R_9 \overset{1}{\succ} R_{11}$

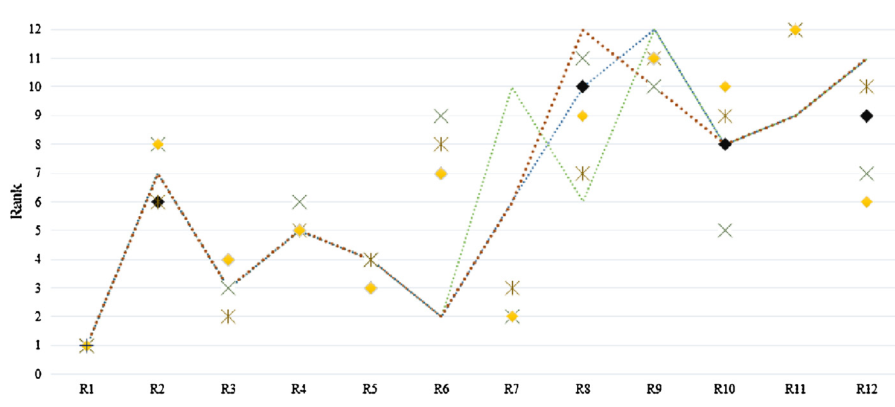

Fig. 3. The effectiveness of aggregation method.

$$u_j^U = \sum_{i=1}^{m} w_i u_{ij}^U, \qquad j = 1, ..., n. \tag{7}$$

where, w_i (i = 1, . . . , m) is the relative weight of the ith ranking method. The related weights are computed by developing the correlation matrix between ranking methods indicated in Table 19. The normalized sum of each method's correlation is taken in to account as the weight in Eqs. (6) and (7).

The weighted average utility intervals of the case under study for different values of ε are summarized in Table 20.

The degrees of preferences among the alternatives are calculated based on Eq. (8). More details about the ranking process can be found in Wang et al. (2005).

$$P_{ij} = P(u_i > u_j) = \frac{\max(0, u_i^U - u_j^L) - \max(0, u_i^L - u_j^U)}{(u_i^U - u_i^L) + (u_j^U - u_j^L)}, \qquad i,j = 1, ..., n; i \neq j. \tag{8}$$

The ranking results under different values of ε are presented in Table 21. It is clear that under the assumption of weak order ($\varepsilon = 0$), research center 1 (R1) is rather superior to R7, R3, and R5, but under the strict order ($\varepsilon > 0$), R1, R7 and R3 are quite superior to R5. Whenε takes the maximum value, then R1 is superior to R7 and R3 with 100% confidence. It is recommended to take the maximum value of ε into consideration since the dominant relation between alternatives can be determined to the best degree of preference.

A schematic comparison between different MCDM methods and aggregation ranking results is illustrated in Fig. 3. Where the variation in rankings increase (i.e., R2, R3, and R10) the aggregation ranking results converge to the points within other rankings.

4. Conclusion and further work

The competitive environment of project based RTO necessitates the performance evaluation as decision-making and communication process for improvement to seek the strength and weakness points. To explore these points, BSC is a strategic management system can be used to monitor the performance of the organization with its four perspectives. These perspectives can play a role as the criteria in MCDM techniques as they can be measured in both quantitative and qualitative approaches. Therefore, in this paper, a new aggregation approach based on BSC and four MCDM methods is proposed to evaluate the performance of project based RTO. To take the advantages of the integrated approach and provide greater reliability, RIPI with 12 centers is considered as a real case for this study.

The four perspectives BSC (financial and non-financial) are taken into account to determine the influencing indices for performance evaluation. In the proposed approach, DEMATEL is employed to reflect the interdependencies among four BSC perspectives. To identify the real importance of perspectives and indices (weights) the ANP method is employed.

In the next step, we apply four MCDM methods including ARAS, COPRAS, MOORA and TOPSIS for ranking the alternatives on the basis of the weights acquired by ANP. Decision makers usually select the best alternative based on the ranking orders of MCDM methods. However, different MCDM methods often produce different outcomes for ranking a set of alternative decisions. This is especially difficult when alternatives are very similar to each other. Thus, utility interval aggregation method has been developed to fill the gap and to enhance the reliability of the chosen alternatives. This method is applied to combine the ranking results of four MCDM approaches to prioritize the alternatives. Weighted utility intervals under different discriminant factor are computed by building a correlation matrix between the ranking methods. The results show that maximum value of discriminant factor could determine the best dominant relations between alternatives. The developed approach is applicable to all performance evaluations with simply modifying the related indices.

In summary, according to the above conclusions, for future research the following suggestions are summed up:

1. In this research, the causal relation of the four primary BSC perspectives is explored. It is recommended that a more detailed analysis of the causality structure among indices could be performed.
2. Other MCDM methods could be developed to solve the same problem and to compare with the proposed approach.
3. It is proposed to fuzzify the linguistic information raised by the experts due the uncertainty exists in their opinions.

Appendix A. The preliminaries

Appendix A.1. DEMATEL

The DEMATEL method is employed to visualize the structure of complicated causal relationships between the elements of a system. This method is shown as follows:

Step 1: Find the average matrix.

Suppose h experts are available to solve a problem with n divisions. The resulting matrices for each of the h experts are $\boldsymbol{X}^k$. The (i, j) element of the $n \times n$ average matrix **A** is denoted as a_{ij} calculated by Eq. (A1) (Wang et al., 2012).

$$a_{ij} = \frac{1}{h}\sum_{k=1}^{h} x_{ij}^k, \qquad i,j = 1, ..., n. \tag{A1}$$

Step 2: Construct the direct relation matrix.

The direct relation matrix **D** is obtained by normalizing the average matrix **A**. s is constant calculated by Eq. (A2).

$$s = \min\left[\frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} |a_{ij}|}, \frac{1}{\max\limits_{1 \le j \le n} \sum_{i=1}^{n} |a_{ij}|}\right] \tag{A2}$$

$$\mathrm{D} = s\mathrm{A} \tag{A3}$$

Step 3: Calculate the indirect influence matrix.

The indirect relation matrix **ID** can be obtained from the values in the direct relation matrix **D**. That is,

$$\mathbf{ID} = \mathbf{D}^2 + \mathbf{D}^3 + ... = \sum_{i=2}^{\infty} \mathbf{D}^i = \mathbf{D}^2(\mathbf{I} - \mathbf{D})^{-1} \tag{A4}$$

where **I** is denoted as the identity matrix.

Step 4: Obtain the total relation matrix.

Once the normalized direct relation matrix **D** has been obtained, the total relation matrix **T** can be derived by Eq. (A5),

$$\mathbf{T} = \mathbf{D} + \mathbf{D}^2 + \mathbf{D}^3 + ... = \sum_{i=1}^{\infty} \mathbf{D}^i = \mathbf{D}(\mathbf{I} - \mathbf{D})^{-1} \tag{A5}$$

Step 5: Compute the sum of columns (r_j) and of rows (d_i) in matrix **T** as shown in Eqs. (A6)–(A8).

$$\mathrm{T} = [t_{ij}]_{n \times n}, \qquad i,j = 1, ..., n. \tag{A6}$$

$$d_i = \sum_{j=1}^{n} t_{ij}, \qquad i = 1, 2, \ldots, n. \tag{A7}$$

$$r_j = \sum_{i=1}^{n} t_{ij} \qquad j = 1, 2, \ldots, n. \tag{A8}$$

The value of $(d+r)$ shows the “degree of central role” (importance), indicating the strength of influence of both dispatch and receipt. The higher values of $(d+r)$ the factors have, the more related they are. Similarly, the value of $(d-r)$ shows the “severity of influence,” indicating the prioritization of factors. If $(d-r)$ is positive, then the factor is a “cause-factor,” dispatching the influence to the other factors. If $(d-r)$ is negative, the factor is an “effect-factor,” receiving the influence from the others. The higher values of $(d-r)$ the factors have, the more influence they have on the others.

Step 6: Set threshold value and obtain the influence relation map.

A relation map can be acquired by mapping the dataset of $(d+r, d-r)$, where the horizontal axis $d+r$, and the vertical axis $d-r$. Decision-maker must set a threshold value for the influence level. Only some elements, whose influence level in matrix $\mathbf{T}$ are higher than the threshold value, can be chosen and converted into the map (Wu, 2012).

Appendix A.2. ANP

ANP, an extension of analytic hierarchy process (AHP), developed by Saaty, provides a way to input judgments and measurements to derive ratio, scale priorities for the distribution of influence among the factors and groups of factors in the decision (Saaty, 2003). The linear structure of AHP extended to ANP. The network relationship of ANP method does not only present the relationship between rules but also calculate the relative weightings (eigenvectors) of each rule. The result of these computations forms a supermatrix. It is also possible to derive the interdependence of criteria and the options and to calculate the weight of criteria and the alternatives.

This method is summarized as follows (Wu et al., 2011).

Step 1: Define problems and establish networked level structure.

Step 2: Form a supermatrix by using criteria comparison. The supermatrix can be accomplished by pairwise comparisons to compare the criteria in the whole system. This is done through pairwise comparisons. The following is the general form of the supermatrix (Eq. (A9)), where C_m represents the mth cluster, and W_{ij} is the principal eigenvector of the effect of the elements compared to the jth cluster to the ith cluster. If the jth cluster has no impact on the ith cluster, then $W_{ij} = 0$. The geometric mean is used to integrate all the experts' subjective preference while a group of experts makes the decision.

$$\mathbf{X} = \begin{array}{c} \\ C_1 \\ \\ C_i \\ \\ C_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & \quad & C_j & \quad & C_n \end{array} \\ \begin{bmatrix} W_{11} & \cdots & W_{1j} & \cdots & W_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ W_{i1} & \cdots & W_{ij} & \cdots & W_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ W_{m1} & \cdots & W_{mj} & \cdots & W_{mn} \end{bmatrix} \end{array} \tag{A9}$$

Step 3: Compute the supermatrix.

The weighted supermatrix is derived by transforming all columns sum to unity exactly. This step is much similar to the concept of markov chain for ensuring the sum of these probabilities of all states equals to 1.

The weighted supermatrix multiplies itself several times and then converges into a limiting supermatrix with a constant value to get the global priority vectors or called weights.

The relative weights of all criteria obtained in the limiting supermatrix can then be integrated with the evaluation scores (performance value) of the alternatives assessed by the specialists to find the best alternative.

Appendix A.3. MOORA

The MOORA method introduced by Brauers and Zavadskas (2006) is recently applied in several studies as an MCDM method. This method consists of two elements: the ratio system and the significance coefficient with the following steps:

Step 1: Construct a decision matrix ($\mathbf{X}$) containing the performance of m alternatives on n attributes.

$$\mathrm{X} = \begin{bmatrix} x_{11} & \ldots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ x_{i1} & \ldots & x_{ij} & \ldots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \ldots & x_{mj} & \ldots & x_{mn} \end{bmatrix}, \tag{A10}$$

where x_{ij} is the performance measure of alternative ith on attribute jth.

Step 2: Calculate the ratio value. The best choice of ratio system is the square root of the sum of squares of each alternative per attribute according to Brauers et al. (2008) and Chakraborty (2011). The ratio is expressed as below:

$$\hat{x}_{ij} = \frac{x_{ij}}{\left[\sum_{i=0}^{m} x_{ij}^2\right]^{1/2}}, i = 1, \ldots, m; j = 1, \ldots, n. \tag{A11}$$

where $\hat{x}_{ij}$ is a dimensionless number in the interval of [0,1] which represents the normalized performance of alternative ith on attribute jth. The ratio system calculates the overall performance of each alternative as the difference between the sums of its normalized performances.

Step 3: For multi-objective optimization, these responses are added in case of maximization and subtracted in case of minimization based on Eq. (A12).

$$Y_j = \sum_{j=1}^{k} \hat{x}_{ij} - \sum_{j=k+1}^{n} \hat{x}_{ij}, j = 1, \ldots, n. \tag{A12}$$

where k is the number of attributes to be maximized.

To show the significance of each attribute, the weights are taken into consideration (significance coefficient). Thus, Eq. (A12) becomes Eq. (A13).

$$Y_j = \sum_{j=1}^{k} w_j \hat{x}_{ij} - \sum_{j=k+1}^{n} w_j \hat{x}_{ij}, j = 1, \ldots, n. \tag{A13}$$

The Y_j value could be positive or negative depending on the beneficial and non-beneficial attributes in the decision matrix. Therefore, the best alternative has the highest value.

Appendix A.4. ARAS

ARAS method as an MCDM method is proposed by Zavadskas and Turskis (2010). The following steps show the procedure:

Step 1: The first stage is decision-making matrix (DMM) forming. The following DMM of preferences (x_{ij}) for m alternatives (rows) rated on n sign full criteria (columns):

$$X = \begin{bmatrix} x_{01} & \dots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ x_{i1} & \dots & x_{ij} & \dots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mj} & \dots & x_{mn} \end{bmatrix}, \tag{A14}$$

x_{0j} is the optimal value of j criterion.

If optimal value of j criterion is unknown, then

$$x_{0j} = \max_i x_{ij}, \text{ if } \max_i x_{ij} \text{ is preferable and } x_{0j} = \min_i x^*_{ij}, \text{ if } \min_i x^*_{ij} \text{ is preferable} \tag{A15}$$

The performance values x_{ij} and the criteria weights w_j are viewed as the entries of a DMM. The system of criteria as well as the values and initial weights of criteria are determined by experts.

In order to avoid the difficulties caused by different dimensions of the criteria, the ratio to the optimal value is used.

Step 2: The initial values of all the criteria are normalized.

$$\overline{X} = \begin{bmatrix} \overline{x}_{01} & \dots & \overline{x}_{0j} & \dots & \overline{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{x}_{i1} & \cdots & \overline{x}_{ij} & \cdots & \overline{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{x}_{m1} & \cdots & \overline{x}_{mj} & \cdots & \overline{x}_{mn} \end{bmatrix} \tag{A16}$$

The criteria, whose preferable values are maxima, are normalized as follows:

$$\overline{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}, i = 0, \dots, m; \qquad j = 1, \dots, n. \tag{A17}$$

The criteria, whose preferable values are minima, are normalized by applying two-stage procedure:

$$x_{ij} = \frac{1}{x^*_{ij}}, i = 0, \dots, m; \qquad j = 1, \dots, n. \tag{A18}$$

$$\overline{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}, i = 0, \dots, m; \qquad j = 1, \dots, n. \tag{A19}$$

Step 3: The normalized-weighted matrix is defined in this step. It is possible to evaluate the criteria with weights $0 < w_i < 1$. The values of weight w_j are usually determined by the expert evaluation method ($\sum_{i=1}^{n} w_j = 1$).

$$\hat{X} = \begin{bmatrix} \hat{x}_{01} & \dots & \hat{x}_{0j} & \cdots & \hat{x}_{0n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ \hat{x}_{i1} & \dots & \hat{x}_{ij} & \dots & \hat{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \dots & \hat{x}_{mj} & \dots & \hat{x}_{mn} \end{bmatrix}, i = 0 \dots m; j = 1 \dots n. \tag{A20}$$

Normalized-weighted values of all the criteria are calculated as follows:

$$\hat{x}_{ij} = \overline{x}_{ij} \times w_j, i = 0 \dots m; \qquad j = 1 \dots n. \tag{A21}$$

where w_j is the weight (importance) of the j criterion and x_{ij} is the normalized rating of the j criterion.

Step 4: The following task is determining values of optimality function:

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}; i = 0, \dots, m. \tag{A22}$$

where S_i is the value of optimality function of i alternative.

The biggest value is the best, and the least one is the worst. Therefore, the greater the value of the optimality function S_i, the more effective the alternative.

The priorities of alternatives can be determined according to the value S_i. Consequently, it is convenient to evaluate and rank decision alternatives when this method is used.

Step 5: The degree of the alternative utility is determined by a comparison of the variant, which is analyzed, with the ideally best one S_0. The equation used for the calculation of the utility degree K_i of each alternative is given below:

Where S_i and S_0 are the optimality criterion values, obtained from Eq. (A22).

$$K_i = \frac{S_i}{S_0}; i = 0, \dots, m. \tag{A23}$$

It is clear, that the calculated values K_i are in the interval [0,1] and can be ordered in an increasing sequence, which is the wanted order of precedence. The complex relative efficiency of the feasible alternative can be determined according to the utility function values.

Appendix A.5. COPRAS

The COPRAS method is an MCDM method that was introduced by Zavadskas and Kaklauskas (1996). This method determines a solution based on the positive-ideal solution and the negative-ideal solution and therefore can be considered as a compromising MCDM method. Originally, the COPRAS procedure consists of the following steps:

Step 1: Select the influencing criteria describing the alternatives.

Step 2: Prepare the decision-making matrix **X** based on attribute i in the alternative j.

$$X = \begin{bmatrix} x_{11} & \dots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ x_{i1} & \dots & x_{ij} & \dots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mj} & \dots & x_{mn} \end{bmatrix}, \tag{A24}$$

m is the number of attributes; n is the number of the alternatives compared.

Step 3: Determine the weights of the attributes w_i.

Step 4: Normalize the decision-making matrix based on Eq. (A31).

$$\overline{X} = \begin{bmatrix} \overline{x}_{11} & \dots & \overline{x}_{1j} & \dots & \overline{x}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{x}_{i1} & \cdots & \overline{x}_{ij} & \cdots & \overline{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{x}_{m1} & \cdots & \overline{x}_{mj} & \cdots & \overline{x}_{mn} \end{bmatrix} \tag{A25}$$

where $\overline{x}_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij}$.

Step 5: Calculate the weighted normalized decision-making matrix $\overline{X}$. The weighted normalized values $\hat{x}_{ij}$ are calculated by

Eq. (A26).

$$\hat{X} = \begin{bmatrix} \hat{x}_{11} & \dots & \hat{x}_{1j} & \cdots & \hat{x}_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ \hat{x}_{i1} & \dots & \hat{x}_{ij} & \dots & \hat{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \dots & \hat{x}_{mj} & \dots & \hat{x}_{mn} \end{bmatrix}, \tag{A26}$$

where $\hat{x}_{ij} = \bar{x}_{ij} \times w_j, i = 0, ..., m; j = 1, \dots, n$ (w_j is the weight of jth criteria determined in step 3).

Step 6: Determine the maximizing index (P_j: using Eq. (A27)) and minimizing index (R_j using Eq. (A28)) for each alternative from which, maximum value is optimum.

$$P_j = \sum_{i=0}^{k} \hat{x}_{ij}, j = 1, \dots, n. \tag{A27}$$

$$R_j = \sum_{i=k+1}^{m} \hat{x}_{ij}, j = 1, \dots, n. \tag{A28}$$

where k is the number of attributes that should be maximized.

Step 7: Calculate the relative weight of each alternative Q_j.

The highest value of Q_j represents the best alternative.

Appendix A.6. TOPSIS

$$Q_j = P_j + \frac{\sum_{j=1}^{n} R_j}{R_j + \sum_{j=1}^{n} R_j}, j = 1, ..., n. \text{(A29)}$$

TOPSIS is an approach to identify an alternative which is closest to the ideal solution and farthest to the negative ideal solution in a multi-dimensional computing space. A brief description of TOPSIS steps is as follows (Dymova, Sevastjanov, & Tikhonenko, 2013).

Step 1: Construct a decision matrix (**D**) containing the performance of m alternatives with respect to n attributes.

$$D = \begin{bmatrix} d_{11} & \dots & d_{1j} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ d_{i1} & \dots & d_{ij} & \dots & d_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{m1} & \dots & d_{mj} & \dots & d_{mn} \end{bmatrix}, \tag{A30}$$

where d_{ij} is the performance measure of alternative ith on attribute jth.

Step 2: Normalize the decision matrix of **D** using the Eq. (A31) to construct a normalized decision matrix ($\mathbf{N_D}$).

$$n_{ij} = \frac{d_{ij}}{\sqrt{\sum_{k=1}^{m} d_{kj}^2}}, i = 1, ..., m; \qquad j = 1, ..., n. \tag{A31}$$

Step 3: Calculate the weighted normalized decision matrix to construct a weighted normalized decision matrix (**V**).

$$v_{ij} = w_j \times n_{ij}, i = 1, ..., m; \qquad j = 1, ..., n. \tag{A32}$$

where w_j is the weight of criteria jth $(\sum_{j=1}^{n} w_j = 1)$..

Step 4: Determine the positive and negative ideal solutions.

$$A^+ = \{v_1^+, ..., v_n^+\} = \left\{ \max_i v_{ij}, j = 1, ..., n \right\} \tag{A33}$$

$$A^- = \{v_1^-, ..., v_n^-\} = \left\{ \min_i v_{ij}, j = 1, ..., n \right\} \tag{A34}$$

Step 5: Calculate the distance of alternatives from the positive and negative solutions according to Euclidean distances.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)}, i = 1, ..., m. \tag{A35}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)}, i = 1, ..., m. \tag{A36}$$

Step 6: Calculate the relative closeness to the ideal alternatives.

$$RC_i = \frac{S_i^-}{S_i^+ + S_i^-}, i = 1, ..., m \tag{A37}$$

Rank the alternatives according to their relative closeness to the ideal alternatives.

Appendix B. Average score of committee members for BSC indices

BSC Perspectives	Indices	Average Score	Rank
Financial	Cost control	7.1	7
	Contracts value	9.2	1
	Productivity	8.1	5
	Net income	8	6
	Unexpected cost Index	8.7	4
	Net profit rate	8.9	3
	CPI	9.1	2
Customer	Long-term customer retention index	9.5	1
	Market share	8.1	6
	Expanding and development of customers	9	2
	Reputation	7.6	7
	QPI	8.8	4
	Customer complaints	9	3
	Customer trust	8.4	5
Internal process	Employee satisfaction	8.4	6
	SPI	8.7	5
	Set up annual objectives	8.9	4
	Core business process	9	2
	Business opportunities	8.1	7
	Risk management	9.4	1
	Social considerations	7.9	8
	Standard procedure	7.8	9
	After sales services	9	3
Learning and growth	Lessons learned	8.6	4
	Productivity of employees	7.5	8
	Employee turnover	9.1	1
	Employee satisfaction	7.7	6
	Education metrics	8.7	3
	Rewarding system	7.6	7
	Scientific score	8.8	2
	Knowledge management	8.3	5

Appendix C. The relative information of the indices corresponding to the alternatives

	CV	UC	CPI	NPV	CC	LCR	ENC	QPI	ASS	CBP	SMP	RM	SPI	ET	LL	EM	SS
R1	52	1.56	0.53	73	1	8	9	7	8	3	261	0.7	0.78	6	6	10.16	50
R2	24	0.72	0.24	12	2	7	7	5	6	4	67	0.6	0.91	4	5	19.68	60
R3	161	4.83	0.40	21	4	5	4	5	4	5	136	0.7	0.87	5	4	34.50	50
R4	20	0.6	0.10	28	3	7	8	6	5	4	120	0.4	1	5	6	11.21	60
R5	55.8	1.674	0.14	37	4	7	3	5	4	3	130	0.5	0.82	4	5	18.04	65
R6	25.8	0.774	0.12	17	2	7	6	4	5	5	100	0.6	0.47	5	6	20.68	45
R7	61	1.83	0.29	47	1	8	9	5	6	6	130	0.7	0.57	2	7	19.24	70
R8	30	0.9	0.18	19	3	5	6	4	5	4	70	0.4	0.72	6	5	7.82	65
R9	8	0.24	0.23	12	4	5	6	5	6	4	60	0.5	0.91	4	4	9.23	50
R10	5	0.15	0.30	13	3	8	7	4	5	5	85	0.5	0.55	5	4	11.44	55
R11	10.5	0.315	0.08	2	5	6	5	3	4	3	70	0.3	0.87	7	2	32.77	40
R12	6.5	0.195	0.32	16	2	8	6	4	5	4	40	0.4	0.58	6	2	7.42	35

CV = Contracts Value, UC = Unexpected Cost, NPV = Net Profit Value, CC = Customer Complaints, ENC = Expanding of New Customer, LCR = Long-term Customer Retention, ASS = After-Sales Service, CBP = Core Business Process, SMP = Setting up Major Programs, RM = Risk Management, ET = Employee Turnover, LL = Lessons Learned, EM = Education Metrics, SS = Scientific Score.

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