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A novel dynamic credit risk evaluation method using data envelopment analysis with common weights and combination of multi-attribute decision-making methods

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ABSTRACT

Credit risk evaluation is always the most important factor in determining Customers' credit status in financial institutions. Multi-Attribute Decision-Making (MADM) methods have been widely used in this field. But most of the studies neglect the undeniable impact of time and changes of the credit assessment criteria, their importance and evaluation data over time. On the other hand, developed Dynamic MADM (DMADM) methods often used subjective weighting methods and then applied some aggregation operators to rank alternatives. This paper proposes a new combination of Data Envelopment Analysis (DEA) as a powerful objective weighting method with DMADM as a novel dynamic decision-making method for credit performance evaluation. For this aim, the credit performance criteria were extracted using literature review and experts' views. Criteria weights were calculated with dynamic DEA common set of weights approach. Then, the applicants are prioritized using five Grey MADM methods (including SAW-G, VIKOR-G, TOPSIS-G, ARAS-G and COPRAS-G). Finally, a new method called Correlation Coefficient and Standard Deviation (CCSD) was used to determine the final aggregated rank. This novel method is applied in order to credit ratings of the clients in the Beekeeping Industry Development Funding Institute IRAN The results indicate that the proposed MADM method, while eliminating the limitations of previous methods, has been able to maintain robustness. Also, the results are highly correlated with the results of previous methods.

1. Introduction

The economic and social well-being of countries highly depend on the performance of financial institutions (Burak Emel et al., 2003). Financial loans play a vital role in financing industries. Banks and financial institutions provide credit to support manufacturing, agricultural, commercial, and service enterprises (Bahabadi and Mohammadi, 2016). Usually, bank loans are one of the main modes of firms financing Cao et al. (2019). Thus, their failures, send seismic waves affecting the social status of the country and have the potential of a quick global impact (Bessis, 2001). Different industries need to access financial sources to develop and maintain their activities. The role and importance of bank loans in the economic and industrial development of both production and service industries are signified in studies. Hassan and Olaniran (2011) and Ifeakachukwu (2013) emphasized the important role of bank financimg in the industrial activities development. Motta and Sharma (2020) examined the importance of financing in the hospitality industry. Zavadska (2018) studied the role of banks in the innovative development of economies. This study signifies the important role of banks participation in economic growth. Liu et al. (2019) also extracted the role of bank loans in promoting technological innovation of companies. Without any doubt, the bank loans play an important and inevitable role in financing industrial activities.

On the other hand, borrowing too? risky and hard to value businesses and loan applicants encounter great risks. Generally, default risk is defined as the possibility of not fulfilling a contractual

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commitment by the counterparty in a financial contract (Bielecki and Rutkowski, 2013, Bluhm et al., 2016). Koju et al. (2020) found that the development of industrial and export sectors are the main drivers of loan performance in developed countries and proposed an expansionary fiscal policy to enhance per capita income and productivity to assure the banking system. This study highlights the direct role of the banking system on industrial development while implying the importance of assuring banking systems from potential risks. Banking crises have some severe and deep impact on different measures, as studied by Wilms et al. (2018). Besides the impacts of the banking crises, its man drivers can be considered. Different studies reported several drivers and causes of the banking crisis (Heilpern et al., 2009, Ahrend and Goujard, 2011). Credit risks are one of the main causes of banking crises. Vodová (2003) highlighted the role of credit risk in banking crises. Njanike (2009) examined the effect of failure to credit risk assessment on banking crisis. Credit risk usually occurs as a consequence of different factors. Among recent studies, Kavussanos and Tsouknidis (2016) found that Industry-specific variables include current and expected conditions; the risk appetite of borrowers and a pricing variable are the main drivers of default risk in shipping bank loans. Mpofu and Nikolaidou (2018) investigated 22 sub-Saharan African countries and determined that GDP growth, inflation rate, credit to the private sector as a percent of GDP, and trade openness have a significant impact on credit risks.

Therefore it seems that there is a dilemma to tradeoff between the role and need of industries to financial loan on one side and the latent and inevitable risks implied in loaning. To respond to this challenge, banks and financial institutes apply credit scoring to assess the credibility of their customers. These studies classified credit applicants into some groups according to their repayment behavior (Ha and Krishnan, 2012). Due to the limited financial resources and facilities available to the banks and financial institutions, assessment of the ability of customers to repay before lending them is one of the most important challenges for improving the country's banking system (Bahabadi and Mohammadi, 2016). As a result, financial risk forecasting becomes an even more important task today (Li and Zhong, 2012; Chen et al., 2020) and it is inevitable to make lending/ credit decisions as cautious as possible with an emphasis on efficiency and effectiveness of decision-making process (Burak Emel et al., 2003; Kozeny, 2015). However, it should be noted that a strict and conservative credit evaluation will deprive eligible firms to access their required financial resources (Dekkers et al., 2020).

Traditionally, deciding to grant a credit was made by the human judgment to appraise the default risks (Thomas, 2000). But due to the insufficiency of this approach and the high importance of credit evaluation in financial institutions, making decisions in this area is highly risky (Zakrzewska, 2007). Also, the increase in the demand for credit, causes a larger concern to more structured and objective credit scoring methods to help credit providers decide to grant credit to an applicant or not (Akhavein et al., 2005).

Since then, several methods have been emerged to evaluate the credit performance. Some of these methods are statistical and mathematical, e.g. support vector machines (Zhang et al., 2014), decision trees discriminant analysis (Altman, 1968) and logistic regression (Lee et al., 2006), while others rely on artificial intelligence (AI) approaches; e.g. inductive learning (Han et al., 1996), artificial neural networks (Lee and Chen, 2005; Akkoç, 2012), genetic algorithms (Kozeny, 2015; Huang and Tzeng, 2006) and artificial immune system (Chang and Yeh, 2012).

Regarding the pitfalls of the various techniques available for the evaluation of credit performance, including the need for a large amount of historical data (Burak Emel et al., 2003), complicated and costly computations (Marqués et al., 2013) and the necessity of considering several financial and non-financial criteria in credit performance evaluation problems (Yurdakul and Tansel I'c, 2004) which all of them might not be qualitative (Tomić-Plazibat et al., 2006) and also, each of criteria might have a different importance degree or weight (Razavi Hajiagha et al., 2018), various researches have suggested using multi-criteria based methods as a powerful approach in credit performance evaluation (Che et al., 2010; Abdollahi et al., 2014; Barak and Heidary Dahooei, 2018; Salih et al., 2019).

The main contribution of the current study can be considered as proposing a dynamic multi-criteria credit scoring framework along with applying an exact criteria weight elicitation method used with a series of Multi-Attribute Decision-Making (MADM) methods to improve the credibility of the results. One of these concerns deals with the dynamicity of credit performance evaluation problems. Since credit evaluation can be considered as forecasting the future behavior of a loan applicant, the credit scoring method should have the ability to infer the behavior of an applicant according to its historical performance rather than relying only on a single period of time. This paper tries to emphasize the longitudinal nature of credit scoring instead of a cross-sectional viewpoint. Secondly, considering the importance and sensitivity of criteria weights in credit scoring, an exact and analytical method to extract these weights from the available dataset of applicants is crucial. This method can prevent any bias in the subjective weights assigned to the credit scoring criteria. Finally, considering the heuristic nature of MADM methods and their capability in identifying Pareto-optimal solutions rather than unique global optima, analyzing the problem by a single method is not adjustable. Thus, the proposed framework is developed using a variety of MADM methods to reach an aggregated and admissible solution.

The aim of this paper is to propose a framework evaluate the credit performance of loan applicants according to their performance in a specific time horizon. Practically, the framework composed a dynamic MADM approach reinforced with a dynamic Data Envelopment Analysis (DEA). Common Set of Weights are used to determine the criteria weights. In this regard, to avoid losing data, the obtained data in different time periods are aggregated through Chebyshev inequality bounds to form a grey decision-making matrix. After that, the alternatives are ranked using different Grey MADM methods. Then, a new combination method using CCSD is proposed to identify the final rank. Finally, the results are discussed and sensitivity analysis is performed in the last section.

The paper is organized as follow. The related literature is reviewed in section 2. A brief introduction and review on MADM is given in section 3. The proposed hybrid dynamic DEA common set of weights – DMADM based framework for firms' credit evaluation is described in section 4. The application of the proposed framework in a real-world case study is represented in section 5. Finally, the paper is concluded in section 6.

2. Literature review

Credit evaluation is defined as the collection, analysis, and classification of different credit characteristics and variables to assess the credit risk (Abdou and Pointon, 2011). It is defined as the probability that the debtor will not pay the interest and/or reckoning of the principal in due date for payment. It has been recognized as one of the main causes of financial institutes' bankruptcy (Tomić-Plazibat et al., 2006).

Due to the fundamental role of credit performance evaluation in the financial sector, several methods have been developed for credit risk decisions (Lessmann et al., 2015). So, regarding the previous researches, all of the credit scoring methods can be generally categorized into five categories including statistical techniques, Multi-Attribute Decision-Making theories (MADM), Data Envelopment Analysis (DEA), machine learning (Zhu et al., 2019), Support Vector Machine (SVM) (Kim and Ahn, 2012), and Artificial Neural Networks (ANN) (Zhang et al., 2016). Some of the recent researches are introduced for each category in Table 1.

It is obvious that each category has its strengths and it could be practical in solving many problems. However, statistical techniques, AI and SVM based methods require a large amount of data to produce valid and acceptable results (Burak Emel et al., 2003). On the other side, due to the high complexity of calculation and implementation of these methods, they need professional experts and special software which increases the costs of calculation (Marqués et al., 2013). The problem of evaluating a firm's credit performance is a complex one that has to be considered with several financial and non-financial criteria to make the most optimal decision (Yurdakul and Tansel I'c, 2004; Tomić-Plazibat et al., 2006).

MADM and DEA are a class of robust and well-known tools capable of considering several criteria for evaluation when dealing with complex decision problems and several and possibly conflicting financial or non-financial criteria are considered (De Lima Silva et al. (2018); Ferreira (2015)). Also, these methods are capable of implementation with a limited set of data points (Cheng et al., 2007) and due to their simplicity, they can be used by the non-expert decision-makers (Zhang et al., 2016). So, in recent years, these methods have received great attention from the researches for credit evaluation problems. Table 2 shows some of the previous studies to evaluate the credit performance. Due to the importance of the evaluation criteria, they are also introduced.

According to the literature review, DEA and MADM methods are applied to evaluate the credit performance but they have some limitations (Sinuany-Stern et al., 2000) which lead the previous researches to use the combination of them (Abdollahi et al., 2014; Barak and Heidary Dahooei, 2018). The combination of these methods which takes the advantages of both by avoiding their pitfalls (Sinuany-Stern et al., 2000) is rarely applied for the credit evaluation.

Investigation of the previous researches reveals some concerns and flaws which are described below:

First, Although various researchers have emphasized the dynamicity of the credit performance evaluation (Li and Zhong, 2012), the majority of the proposed methods are static. Also, they consider exact values for the outputs and inputs of the problem, while the actual values of these factors are usually inaccurate (Li and Zhong, 2012), interval, or are determined according to different scenarios over time (Zahedi-Seresht et al., 2016). Therefore, the single-period credit performance evaluation models are not sufficient, and comparing the performance of applicants over multiple time periods is considerable (Razavi Hajiagha et al., 2015). This concern is not considered in previous studies.

Table 1
Credit scoring methods.

Methods	Researches
Statistical techniques	(Genriha and Voronova, 2012; Hand and Henley, 1997; Lee et al., 2006; Bolton, 2009; Heiat, 2014; Kozeny, 2015; Georgios, 2019; Moradi and Mokhatab Rafiei, 2019; Ogundimu, 2019)
Multi attribute decision making theories	(Bryant, 2001; Yurdakula and Tansel Iç, 2004; Tomić-Plazibat et al., 2006; Zhang et al., 2010; Xia et al., 2017; Sun et al., 2017; Yang et al., 2019)
Artificial neural networks	(West, 2000; Pavlenko and Chernyak, 2010; Akkoç, 2012; Bequé and Lessmann, 2017; Huang et al., 2018; Shen et al., 2019)
Support vector machine	(Schebesch and Stecking, 2005; Huang et al., 2007; Bellotti and Crook, 2009; Zhang et al., 2014; Harris, 2015; Jiang et al., 2018; Pławiak et al., 2019; Yontar et al., 2020)
Data envelopment analysis	(Burak Emel et al., 2003; Shanmugam and Johnson, 2007; Psillaki et al., 2010; Premachandra et al., 2011'; Avkiran, 2011; Iazzolino et al., 2013; Tsolas, 2015; Huang et al., 2018; Zhang and Wang, 2018; Zhou et al., 2019; Zhu et al., 2020)

Second, MADM refers to selecting the best alternative from a finite set of alternatives evaluating based on multiple usually conflicting attributes (Wang and Luo, 2010; Liu and Wang, 2020). This evaluation is usually done to reach a goal or fulfill a purpose (Issa et al., 2019). An important element of MADM problems is the weights of attributes. Therefore, determining these weights is very crucial (Wang and Luo, 2010; Barak and Heidary Dahooei, 2018; Liu and Teng, 2019; Liu et al., 2021). According to literature, two main approaches are used to determine the criteria weights: experts' judgments-based (subjective) and data-based (objective) (Wang and Lee, 2009). While subjective methods merely rely on the preferences of decision-makers (Burak Emel et al., 2003), objective methods, e.g. entropy, CCSD, SD, extract the weights using objective decision matrix information. In this case, the subjective judgment or intuition of the decision-makers do not affect the criteria weights (Barak and Heidary Dahooei, 2018). Also, it might be possible that the decision-maker suffers from stress or gets confused (for a large number of criteria) that can lead to inconsistency (Ma et al., 1999).

Considering the sensitivity and importance of decision making in credit scoring (Zakrzewska, 2007), the objective methods would be more efficient in such problems. The previously developed objective methods, like entropy, standard deviation, and CCSD are often based on statistical characteristics including redundancy or probability, dispersion, or data correlation. Thus they need a large amount of data and statistical presumption about these data (Burak Emel et al., 2003). Barak and Heidary Dahooei (2018) applied DEA as an objective method to calculate the criteria weights. This idea is extended in this paper for the Dynamic MADM approach using the Dynamic DEA as a robust objective method of calculating the credit performance criteria weights. Since it is expected to have similar weights for a criterion in different periods, the dynamic common set of weights approach (Razavi Hajiagha et al., 2018) is applied in the proposed method.

Third, Another issue of the application of MADM methods is that each of them has its benefits and in the case of the same problem, they may lead to different results (Barak and Heidary Dahooei, 2018). Therefore, the application of a single method cannot ensure obtaining the best result (Akhavan et al., 2015; Zavadskas et al., 2016a, 2016b). So, the selection of the best MADM method would be challenging for the researchers. In this respect, some studies have applied a combination of MADM methods to evaluate the credit performance (Sun, 2010); and have found this combination more efficient in increasing the accuracy of the final decision (Barak and Heidary Dahooei, 2018). However, no research considers the importance of MADM methods combination in the case of credit performance evaluation. In this paper, a combination of MADM methods is used and their results are aggregated using the CCSD method (Barak and Heidary Dahooei, 2018).

To address the aforementioned concerns, first of all, a list of credit evaluation criteria is gathered through reviewing the literature. Then, the dynamic MADM approach is applied to score the credit performance of each applicant firms. In this regard, the dynamic DEA model with a common set of weights (CSW) approach is used to determine the criteria weights. To this aim, using Chebyshev inequality bounds, multi-period information is transformed into an interval decision matrix and a variety of interval MADM methods are used to appraise the credit applicants. Finally, the results of different MADM methods are combined using the CCSD method.

Table 2
Literature review on credit scoring researches.

Authors	Case study	Criteria for credit evaluation	Weighting method	Prioritizing method
Zhu et al. (2020)	Prediction of effective customers of internet financial loan products	Age, sex, registration channels, loan score, credit score, fund score	–	DEALG (DEA and Logistic Regression)
Zarei Mahmoudabadi and Emrouznejad (2019)	Evaluation of operational, service, and social effectiveness for 37 branches of a commercial bank in Iran	**inputs:** employees, fixed assets, and non– operating costs; **outputs:** Employment, interest income, non–interest income, Number of transactions and Number of accounts	–	Network DEA (Three-stage SBM model)
De et al. (2019)	Credit assessment of electricity retailing companies	4 main criteria (external basic environmental, operational, financial and transaction credit risk factors) which include 22 sub criteria	Intuitionistic fuzzy AHP (IFAHP)	IFAHP
Tansel İç (2019)	Loan applicants firms in one of the commercial banks of Turkey	1. Operating efficiency and profitability ratios 2. Capital structure and long-term solvency ratios 3. Short-term liquidity ratios	Experts' opinion	MOORA Method and Goal Programming
Rus (2018)	Fuzzy performance Evaluation in Romanian Banking Industry	1. Banking network 2. Sustainable development 3. Credit products 4. Profits 5. Innovation 6. E-banking performance	Fuzzy AHP	Fuzzy TOPSIS
Shen et al. (2018)	Credit risk evaluation of 5 potential strategic partners of a financial enterprise	Character (C1), Capacity (C2), Capital (C3), Collateral (C4) and Condition (C5).	Maximizing deviation method	Intuitionistic fuzzy TOPSIS
Bahabadi and Mohammadi (2016)	Credit scoring for Refah Bank of Yazd customers in Iran	Income, The and the type of collateral, Average inventory, The duration of relation with the bank, work experience, etc.	AHP	TOPSIS
Gutiérrez-Nieto et al. (2016)	Credit scoring for a social entrepreneur company	3 major criteria (payment history to partners, financial institutes and suppliers) including: 1. operational profitability 2. Long-term solvency 3. short-term liquidity	AHP	AHP and Geometric mean
Tansel İç and Yurdakul (2010)	Manufacturing firms in Turkey	1. Operational profitability 2. Long-term solvency 3. short-term liquidity	Experts' opinion	Fuzzy TOPSIS
Lou et al. (2007)	Credit scoring for 32 different countries	Current account balance as percentage of GDP, Exports average annual growth rate, Imports average annual growth rate, GDP per capita, etc.	AHP	UTADIS (Dynamic)
Che et al. (2010)	Loan applicant small and medium enterprises in Taiwan	**Inputs:** 1. Total liabilities/net profits 2. Interest expenses/operating income 3. Short-term bank loan/operating income, etc.; **Outputs:** 1. Operating activity cash flows/bank 2. short-term loan 3. Liquidity ratio 4. Operating income or account receivables, etc.	Fuzzy AHP	DEA
Psillaki et al. (2010)	Credit scoring for firms in 3 different industries: fabric, wood and paper	inefficiency of the Company, size of the Company, Profitability, Liquidity, debt to asset ratio, Physical assets, Growth and Development	–	DEA and logistic regression
Cheng et al. (2007)	Credit evaluation of loan applicants	(**Inputs:** 1. Concession period 2. Financial risks to the borrower; **Outputs:** 1. Tariff/toll setting up and adjustment mechanism 2. Total investment schedule 3. Attractiveness of main loan agreement, etc.)	–	DEA
Tomić-Plazibat et al. (2006)	Credit scoring for some commercial firms in Croatia	1. Profitability 2. Solvency 3. Liquidity	AHP	PROMETHEE
Yurdakula and Tansel Iç (2004)	credit performance evaluation of the manufacturing firms in Turkey	1. Operational profitability 2. Long-term solvency 3. Short-term liquidity	AHP	AHP
Burak Emel et al. (2003)	credit performance evaluation of 82 industrial/manufacturing firms in turkey	DEA (**inputs:** 1. Short term bank loans/current liabilities 2. Current liabilities/net sales 3. ABS=|1–(Fixed assets/owners' equity)| **Outputs:** 1. Liquidity ratio= (current assets-inventories)/current liabilities. 2. Owners' equity/total assets 3. Net profit/total assets)	–	DEA

3. Dynamic Multi-Attribute Decision-Making (DMADM)

MADM is the problem of ranking a finite set of alternatives based on multiple, usually, conflicting criteria (Barak and Heidary Dahooei, 2018; Liu and Wang, 2018). Traditionally, MADM methods mostly focused on a single period of evaluation. However, the decision-making matrix data, criteria importance degree, and even experts' committee may differ during different periods of time. Also, sometimes, the decision-makers have to consider both the current and past performance of alternatives. Adding the time dimension to classic MADM; these problems are called dynamic multi-attribute decision making (DMADM) problems (Zhang, 2012). The main aspect of DMADM is to gather input arguments from different periods. DMADM problems are popular in multi-stage investment decision making, medical diagnosis, personnel dynamic evaluation, and military systems evaluation, etc. (Xu, 2009, 2008; Chen and Li, 2011). DMADM problems are obviously more complex than MADM problems and have become an important topic in decision-making fields (Lin et al., 2008).

As mentioned before, since the credit performance should be evaluated according to various criteria or attributes, during different periods of time (Yurdakula and Tansel Iç, 2004), it is a DMADM problem.

DMADM firstly was introduced in the 1980s (Hashemkhani Zolfani et al., 2016). Then, Leong (1998) worked specifically on responding to the needs in DMADM. Time and uncertainty have been considered as different elements in the model. Later, Salo et al. (2003) proposed new perspectives in technology foresight about evaluating R&D projects. After that, DMADM problems have been investigated by many researchers regarding their high practicality (Xu, 2008). Table 3 shows some of the previous DMADM researches.

According to the table above, objective methods are rarely applied in order to determine criteria weights. Besides that, most of the previous researches ranked the alternatives separately in different periods of time and then aggregated the results using the common aggregation functions. While this approach neglects the data changes during the time and therefore it has some pitfalls.

So in this study, a combination of Dynamic DEA, Chebyshev inequality bounds, and interval MADM is proposed in order to make decisions in a dynamic environment. Until 1988, MADM and DEA were entirely separated (Adler et al., 2002). Both of these methods have some potential disadvantages. Originally, evaluating based on a set of criteria (inputs and outputs), DEA categorized DMUs into two classes of efficient and inefficient units without ranking them (Sinuany-stern et al., 2000). On the other hand, while DEA is able to handle hundreds of alternatives, some MADM methods like AHP or ANP, which act on pairwise comparisons work on a limited number of alternatives (Sarkis, 1999).

To overcome these limitations, DEA and MADM methods are hybridized in different studies, e.g. Sinuany-stern et al. (2000), Zhao et al. (2006), Fallah Jelodar (2016), and Barak and Heidary Dahooei (2018) combined DEA and MADM methods dealing with decision-making problems. In some of these studies, MADM methods are used to calculate criteria weights. Then, the managerial preferences are integrated into the DEA model by restricting DEA weights using the calculated weights (Abdollahi et al., 2014; Sarkis, 1999).

However, Barak and Heidary Dahooei (2018) used DEA to calculate the criteria weights and ranked the alternatives based on these criteria. Implementing their approach for airline evaluation, they demonstrated the efficiency of DEA as a robust objective weighting method. Given the specific features of this approach, in this paper, DEA is used to calculate the weights of credit performance evaluation criteria. However, their proposed approach is a single-period method and it should be extended to a multi-period mode. DEA provides different set of weights for criteria per alternatives. This will make the decision-making process frustrating. Therefore, in this paper the multi-period common set of weights are used to determine criteria weights.

4. A dynamic multi-attribute decision-making framework for credit scoring

This study aims to provide a novel dynamic decision-making method, combining the dynamic DEA model with a common set of weights and interval MADM methods to evaluate the credit performance of loan applicants. As mentioned, both DEA and MADM methods individually have limitations; nevertheless, an integrated model considering the time and changing data during different time periods is proposed. The proposed method is organized into four phases, as shown in Fig. 1.

The first phase is to calculate credit performance evaluation criteria weights. In this phase, initially an expert committee is formed. Then, a list of credit evaluation criteria is gathered through reviewing the literature. These criteria are shared and finalized by the expert committee. Considering the context of DEA, these criteria are divided into two categories of positive and negative criteria. Considering the dynamic nature of credit performance evaluation, the data regarding each applicant is obtained in the considered timeframe, for each period. Then, the criteria weights are calculated using dynamic common set of weights DEA model.

The second phase is to transform the multi-period decision matrices into a single decision matrix. This transformation is done using the Chebyshev inequality bounds.

The third phase is to evaluate dynamic credit performance. The credit performance scores of applicants are analyzed using different MADM methods.

The fourth phase is to combine the results and rank applicants. In this phase, the CCSD method is used to combine the results of different MADM methods. For this purpose, after constructing the matrix containing the scores of decision-making units (DMUs) in each of the MADM methods, the weight of each method was calculated using CCSD and then the final score of applicants were calculated and the final rating of each is determined.

4.1. Criteria weight calculation

In the proposed methodology, DEA is used as a powerful objective method to determine the weights of criteria. DEA was initiated by Charnes et al. (1978) (CCR model). It provides a framework to evaluate the relative efficiency of a set of homogeneous DMUs (Barak and Heidary Dahooei, 2018) which use a vector of inputs to produce a set of outputs (Razavi Hajiagha et al., 2008). No assumption about system structure is required in DEA (Ang and Chen, 2015), and therefore, it is widely applied in various domains (Emrouznejad and Yang, 2018). Cook and Seiford (2009) presented a comprehensive review of the theoretical backgrounds of DEA.

The DEA problem can be structured as a set of n DMUs, $DMU_j, j = 1, 2, \cdots, n$ each one consumes a semi-positive m-dimensional input vector $x_j = (x_{1j}, \cdots, x_{mj}) \geq 0$, and $x \neq 0$ to produce an s-dimensional semi-positive output vector $y_j = (y_{1j}, \cdots, y_{sj})$, and $y_j \neq 0$. The CCR model to evaluate the $DMU_0, 0 \in \{1, 2, \cdots, n\}$ is formulated as:

$$\begin{aligned} &\text{Max} \sum_{r=1}^{s} \mu_r y_{r0} \\ &\quad \text{s.t.} \\ &\sum_{i=1}^{m} v_i x_{i0} = 1 \\ &\quad \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, j = 1, 2, \cdots, n \;\; v_i \geq \varepsilon, i = 1, 2, \cdots, m \\ &\mu_r \geq \varepsilon, r = 1, 2, \cdots, s \end{aligned} \tag{1}$$

where v_i and μ_r illustrate the weights of ith input and rth output respectively, and ε

is a positive infinitesimal non-Archimedean value to avoid weights getting zero. As it can be seen, DEA provides a desirable condition for the DMUs to maximize their relative efficiency by taking the most desirable weights of inputs and outputs.

It might be possible that approximating the efficiencies with this weighting scheme can overestimate the real-world efficiency of DMUs (Razavi Hajiagha et al., 2008). Davoodi and Zhiani Rezai (2012) discussed the problems due to this type of weighting. Besides, this is a single-period approach and as mentioned before, the single-period credit performance evaluation models are not efficient in credit assessment (Razavi Hajiagha et al., 2015; Xu, 2008). As described earlier, different approaches are developed to aggregate the weights in dynamic problems such as weighted averaging (Xu, 2008), geometric weighted averaging (Wei, 2009a, 2009b), etc. Since calculating different weights for criteria in different time periods can be misleading, a fixed set of weights is extracted in this study. Therefore, the common set of weights is used. The CSWs problem is a widely studied research stream in DEA responding to full flexibility of weights (Razavi Hajiagha et al., 2018). The goal is to find a common set of weights for the cri-

Table 3
Some of the Dynamic MADM researches.

Operator	Ranking method	Weighting method		Authors
		Criteria	Time	
Fuzzy membership grade and clustering	TOPSIS	Experts' opinion	Experts' opinion	Lin et al. (2008)
Dynamic intuitionistic fuzzy weighted averaging (DIFWA) operator and uncertain dynamic intuitionistic fuzzy weighted averaging (UDIFWA)	TOPSIS	Experts' opinion	Different weighting functions are introduced	Xu and Yager (2008)
Dynamic weighted averaging (DWA)	weighted averaging operator	Experts' opinion	Different weighting functions are introduced	Xu (2008)
Dynamic weighted geometric aggregation (DWGA)	Hybrid geometric aggregation (HGA) operator for closeness coefficient	Experts' opinion	Basic unit-interval monotonic (BUM)	Xu (2009)
Dynamic uncertain weighted geometric averaging (DUWGA)	Dynamic uncertain weighted geometric averaging (DUWGA)	Experts' opinion	Experts' opinion	Wei (2009a)
Dynamic Intuitionistic Fuzzy Weighted Geometric (DIFWG) Operator / uncertain dynamic intuitionistic fuzzy weighted geometric (UDIFWG) operator	interval-valued intuitionistic fuzzy weighted averaging (IIFWA)	Experts' opinion	Experts' opinion	Wei (2009b)
weighted averaging operator	UTADIS	AHP	Entropy	Lou et al. (2007)
dynamic weighted distance (DWD) operator.	weighted distance (WD) operator	linear programming model for maximizing deviation	linear programming model for minimizing the deviation from Entropy	Yao (2010)
Weighted arithmetic averaging operator on TIFNs (TIFN-WAA)	Triangular intuitionistic fuzzy distance	Entropy method	Entropy method	Chen and Li (2011)
Aggregation functions regarding retention policy	Different Aggregation functions are introduced	Experts' opinion	Retention policy	Campanella and Ribeiro (2011)
Dynamic intuitionistic fuzzy weighted averaging (DIFWA) operator,	TOPSIS	Different weighting functions are introduced	Different weighting functions are introduced	Su et al. (2011)
Uncertain time-weighted averaging (UTWA) operator (Based on OWA)	uncertain hybrid weighted aggregation (UHWA) operator	Different weighting functions are introduced	Poisson distribution	Xu (2011)
Ddiscriminative dynamic index	Probabilistic sum operator	Experts' opinion	Experts' opinion	Zulueta et al. (2015)
FIMICA	Full-reinforcement operator (FIMICA)	Experts' opinion	Retention policy	Jassbi et al. (2014)
DAHP	AHP	AHP	–	González-Prida et al. (2012)
Three-dimensional grey interval number relational degree	Three-dimensional grey interval number relational degree	Delphi and AHP	Delphi and AHP	Wang et al. (2014)
dynamic hesitant fuzzy weighted averaging (DHFWA) operators: dynamic hesitant fuzzy ordered weighted averaging (DHFOWA) operator & dynamic hesitant fuzzy ordered weighted geometric (DHFOWG) operator Dynamic hesitant fuzzy hybrid averaging (DHFHA) operator & Dynamic hesitant fuzzy hybrid geometric (DHFHG) operator	HFWA	Experts' opinion	Improved maximum entropy (IME) method & Minimum average deviation (MAD) method	Liao et al. (2014)
DIFWG UDIFWG	GRA TOPSIS	Experts' opinion	Experts' opinion	Bali and Gumus (2014)
DIFWA	Intuitionistic fuzzy distance measures and the closeness coefficient	AHP	Different weighting functions	Bali et al. (2015)
interval-valued intuitionistic fuzzy geometric weighted Heronian means (IVIFGWHM) operator	interval-valued intuitionistic fuzzy geometric weighted Heronian means (IVIFGWHM) operator	continuous ordered weighted averaging (COWA)	Time Weight Based on Time Degree and Information Entropy distance	Yin et al. (2017)
uncertain dynamic interval-valued intuitionistic fuzzy weighted averaging (UDIVIFWA) operator	Interval-valued intuitionistic fuzzy geometric weighted Heronian means (IVIFGWHM) operator	Ideal solution and information entropy	IVIF information entropy	Yin et al. (2018)
Comprehensive prospect value	Prospect theory	Experts' opinion	–	Ma et al. (2019)
Dynamic psychological distance measure	**C**loseness coefficient	Fractional integral, The new value function and the Entropy weight	–	Cheng et al. (2020)

teria used in order to evaluate DMUs' efficiency (Razavi Hajiagha et al., 2008). Various studies have proposed CSW models in a single-period DEA setting (Davoodi and Zhiani Rezai, 2012; Wu et al., 2016; Toloo et al., 2019; Karsak and Goker, 2020).

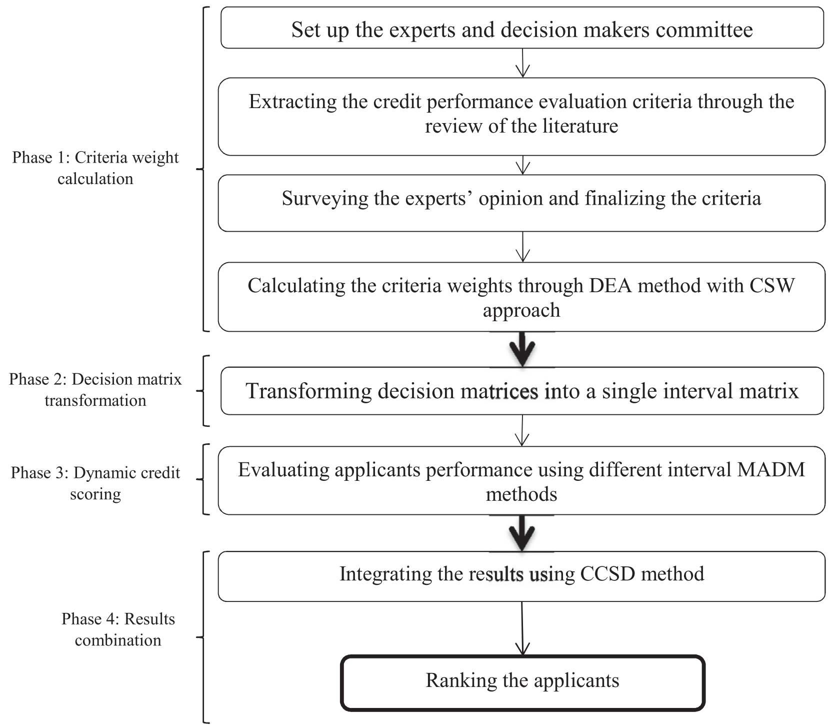

Fig. 1. Hybrid dynamic CSW DEA – dynamic MADM method for credit performance evaluation.

However, since the considered problem is a multi-period decision-making one, in this paper the multi-period CSW weights model proposed by Razavi Hajiagha et al. (2018) is used to determine the criteria weights. The model is formulated as follows:

$$Max\,\frac{1}{M^{+}}\left[\frac{1}{1-\theta_l}\sum_{j=1}^{n}\sum_{r=1}^{s}u_r^c\bar{y}_{rj}-\frac{1}{\varphi_l-1}\sum_{j=1}^{n}\sum_{i=1}^{m}v_i^c\bar{x}_{ij}\right]+\frac{1}{V^{-}}\left[V^{-}-\frac{1}{(1-\theta_l)^2}\sum_{j=1}^{n}\sum_{r=1}^{s}\left(u_r^c\right)^2\delta_{rj}^2-\frac{1}{(\varphi_u-1)^2}\sum_{j=1}^{n}\sum_{i=1}^{m}\left(v_i^c\right)^2\sigma_{ij}^2\right]$$

$$0\leq\frac{1}{1-\theta_l}\sum_{j=1}^{n}\sum_{r=1}^{s}u_r^c\bar{y}_{rj}-\frac{1}{\varphi_l-1}\sum_{j=1}^{n}\sum_{i=1}^{m}v_i^c\bar{x}_{ij}\leq M^{+} \quad (2)$$

$$\frac{1}{(1-\theta_l)^2}\sum_{j=1}^{n}\sum_{r=1}^{s}\left(u_r^c\right)^2\delta_{rj}^2-\frac{1}{(\varphi_u-1)^2}\sum_{j=1}^{n}\sum_{i=1}^{m}\left(v_i^c\right)^2\sigma_{ij}^2\geq 0$$

$$\sum_{r=1}^{s}u_r^c\left(\bar{y}_{rj}+k\delta_{rj}\right)\leq 1, j=1,2,\cdots,n$$

$$\sum_{i=1}^{m}v_i^c\left(\bar{x}_{ij}-k\sigma_{ij}\right)\geq 1, j=1,2,\cdots,n$$

$$u_r^c\geq 0, r=1,2,\cdots,s$$

$$v_i^c\geq 0, i=1,2,\cdots,m$$

It is assumed that n DMUs, $DMU_j, j=1,2,\cdots,n$, are evaluated in a time horizon including T periods, $t=1,2,\cdots,T$. Each DMU, e.g. DMU_j, in each time period t consumes an input vector $x_j^t=\left(x_{1j}^t,x_{2j}^t,\cdots,x_{mj}^t\right)$ and produces an output vector $y_j^t=\left(y_{1j}^t,y_{2j}^t,\cdots,y_{sj}^t\right)$. In model (2), M^{+} is a great number, θ_l and φ_u are DMU-independent thresholds (e.g. they can be considered as equal to input-oriented and output-oriented efficiency of the considered DMU), $\bar{x}_{ij}$ and σ_{ij} indicate the mean and standard deviation of the ith input and $\bar{y}_{rj}$ and δ_{rj} are the mean and standard deviation of the rth output of DMU_j at the whole time horizon, respectively. The vectors $v^c=\left(v_1^c,v_2^c,\cdots,v_m^c\right)$ and $u^c=\left(u_1^c,u_2^c,\cdots,u_s^c\right)$ are respectively the common set of weights for input and output criteria. The above model can be optimized using ordinary optimization packages, e.g. Lingo, GAMS, or MATLAB, while their optimality is assured (Razavi Hajiagha et al., 2018).

In this regard, the loan applicant firms are considered as the DMUs. The negative or cost type criteria are considered as inputs while the positive ones are supposed as the outputs. The common set of weights obtained from the CSW method for these input and output criteria are used as criteria weights in the next steps.

4.2. Decision matrix transformation

Suppose that X is a random variable with an unspecific statistical distribution, where μ and σ, are its mean and standard deviation, respectively. According to *Chebyshev inequality bounds*, this random variable lies in the interval of $(\mu-k\sigma,\mu+k\sigma)$, with a probability of at least $1-1/k^2$ (Ross, 2014, Grinstead and Snell, 2012). letting $k=1/\sqrt{\alpha}$, an approximate $100(1-\alpha)\%$ confidence interval of X is obtained (Razavi Hajiagha et al., 2015).

The proposed framework of credit performance evaluation, as discussed earlier, follows a dynamic and multi-period structure. Suppose that the evaluation criteria denoted as $\{C_1,C_2,\cdots,C_n\}$ are classified into two categories of cost-type criteria, whose lower values are of more interest, defined as input measures called $X=(x_1,x_1,\cdots,x_m)$, and benefit-type criteria, whose larger values are of more interest, defined as output measures called $Y=(y_1,y_2,\cdots,y_s)$. Since loan applicants, DMUs, are evaluated in a horizon of T time periods, therefore each applicant j has its input and output vectors, e.g. $X_i^t=\left(x_{i1}^t,x_{i2}^t,\cdots,x_{ik}^t\right)$ and

$Y_i^t = (y_{i1}^t, y_{i2}^t, \cdots, y_{is}^t), t = 1, 2, \cdots, T$, respectively. Considering D^t as decision matrix of period t, it can be partitioned as $D^t = [X^t, Y^t]$.

Since the number of available data might be limited and the statistical distribution of the available data is unknown, the Chebyshev inequality bounds, in a confidence level of α can be used to transform the individual periods' decision matrices into an interval matrix. The advantage of this method over simply aggregating periodic decision matrices into a single exact matrix is the ability of capturing periodic fluctuations in an interval that includes the values of inputs and outputs with an at least probability of $(1-\alpha)$.

Equation (3) illustrates the proposed formula to transform periods' decision matrices into an overall interval decision matrix. In this formula, $\bar{x}_{ip}, \sigma_{ip}, \bar{y}_{iq}$, and δ_{iq} are mean and standard deviation of pth and qth input and output criteria, respectively.

$$D^1 = \begin{bmatrix} x_{11}^1 & x_{12}^1 & & x_{1k}^1 & y_{11}^1 & y_{12}^1 & & y_{1s}^1 \\ x_{21}^1 & x_{22}^1 & \dots & x_{2k}^1 & y_{21}^1 & y_{22}^1 & \dots & y_{2s}^1 \\ \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots \\ x_{m1}^1 & x_{m2}^1 & & x_{mk}^1 & y_{m1}^1 & y_{m2}^1 & & y_{ms}^1 \end{bmatrix}$$

$$D^2 = \begin{bmatrix} x_{11}^2 & x_{12}^2 & & x_{1k}^2 & y_{11}^2 & y_{12}^2 & & y_{1s}^2 \\ x_{21}^2 & x_{22}^2 & \dots & x_{2k}^2 & y_{21}^2 & y_{22}^2 & \dots & y_{2s}^2 \\ \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots \\ x_{m1}^2 & x_{m2}^2 & & x_{mk}^2 & y_{m1}^2 & y_{m2}^2 & & y_{ms}^2 \end{bmatrix}$$

$$\vdots$$

$$D^T = \begin{bmatrix} x_{11}^T & x_{12}^T & & x_{1k}^T & y_{11}^T & y_{12}^T & & y_{1s}^T \\ x_{21}^T & x_{22}^T & \dots & x_{2k}^T & y_{21}^T & y_{22}^T & \dots & y_{2s}^T \\ \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots \\ x_{m1}^T & x_{m2}^T & & x_{mk}^T & y_{m1}^T & y_{m2}^T & & y_{ms}^T \end{bmatrix}$$

$$\boxed{\begin{aligned} \tilde{x}_{ip} &\in [\bar{x}_{ip} - k\sigma_{ip}, \bar{x}_{ip} + k\sigma_{ip}] \\ \tilde{y}_{iq} &\in [\bar{y}_{iq} - k\delta_{iq}, \bar{y}_{iq} + k\delta_{iq}] \end{aligned}} \tag{3}$$

$$\widetilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & & \tilde{x}_{1k} & \tilde{y}_{11} & \tilde{y}_{12} & & \tilde{y}_{1s} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2k} & \tilde{y}_{21} & \tilde{y}_{22} & \dots & \tilde{y}_{1s} \\ \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m1} & & \tilde{x}_{mk} & \tilde{y}_{m1} & \tilde{y}_{m2} & & \tilde{y}_{ms} \end{bmatrix}$$

4.3. Dynamic credit scoring

Different MADM methods are used for credit evaluation, among them can refer to AHP, TOPSIS, UTADIS, MOORA, and PROMETHEE. Essentially, the results obtained from different MADM methods are differed according to their analyzing algorithm (Antuchevičiene et al., 2011). Therefore, selecting and applying the appropriate MADM method for credit performance evaluation is a crucial task. Generally, it seems appropriate to use a combination of MADM methods to solve the decision-making problem. Accordingly, in this paper after constructing the interval grey decision matrix based on periodic decision matrices, different interval grey decision-making methods are used to appraise the applicants' credit performance. Grey systems are extensively used to solve different problems. One of the main advantages of grey numbers dealing with uncertain decision problems is their flexibility (Yazdani et al., 2019). At the end of this step, several performances and ranking scores will be available for the alternatives; each vector corresponds to one of the used methods. While there are no limitations about the method used in this step, a combination of five different interval gray MADM methods, including SAW-G, TOPSIS-G, VIKOR-G, ARARS-G and COPRAS-G are used in the described case study in section 5.

4.4. Results combination

It is mentioned that prioritizing by a single MADM method cannot assure the robustness of the obtained results (Akhavan et al., 2015). Also, if the number of alternatives increases (Olson et al., 1995), or the alternatives perform similarly, the ranking obtained from different MADM techniques might differ significantly that can lead to inconsistency and the validity and reliability of the results can be criticized (Shanian and Savadogo, 2009). In these cases, there is an increasing need for a robust aggregation method, in order to overcome this challenge and increase the robustness of the results (Varmazyar et al., 2016). In this regard, many researchers have suggested the use of a combination of different MADM methods (Sun, 2010).

However, solving the decision-making method using a combination of methods, different results are obtained for applicants. It cannot be expected that all methods reach a similar ranking of applicants. In this context, aggregating different MADM methods is inevitable. According to literature, Borda and Copeland's law are two popular methods for aggregating the results of MADM methods (Pomerol and Barba-Romero, 2012). Varmazyar et al. (2016) proposed a hybrid method based on balanced scorecard (BSC) for combining the results of the ARAS, COPRAS, MOORA, and TOPSIS methods. Wang et al. (2016) presented a hybrid MADM method to combine the results of SAW, TOPSIS, and grey relation analysis (GRA) methods using experimental design. Mousavi-Nasab and Sotoudeh-Anvari (2017) applied DEA as an auxiliary model of selecting a set of alternatives being evaluated by TOPSIS and COPRAS methods.

The previous aggregation methods applied for compounding the results of MADM methods have some shortcomings: These

Table 4
Previous studies credit evaluation criteria.

Criteria	Previous researches	Category
working capital/total capital ratio	Altman (1968), Yurdakula and Tansel Iç (2004), Tansel İç and Yurdakul (2010), Che et al. (2010), Gutiérrez-Nieto et al. (2016), Psillaki et al. (2010), Burak Emel et al., (2003), Cheng et al. (2007)	Output
Owners' equity/total assets	Burak Emel et al. (2003)	
Net income/ working capital	Tomić-Plazibat et al. (2006)	
net income/net sales ratio	Altman (1968), Tomić-Plazibat et al. (2006), Yurdakula and Tansel Iç (2004), Tansel İç and Yurdakul (2010)	
Net sales/owners' equity	Yurdakula and Tansel Iç (2004), Tansel İç and Yurdakul (2010)	
Productivity	Tansel İç and Yurdakul (2010)	
pre-tax income/total capital ratio	Altman (1968), Yurdakula and Tansel Iç (2004), Tansel İç and Yurdakul (2010), Gutiérrez-Nieto et al. (2016), Psillaki et al. (2010), Burak Emel et al. (2003), Cheng et al. (2007), Tomić-Plazibat et al. (2006)	
total liabilities/total assets ratio	Tomić-Plazibat et al. (2006), Yurdakula and Tansel Iç (2004), Tansel İç and Yurdakul (2010), Che et al. (2010), Psillaki et al. (2010),	Input
Tangible assets	Tansel İç and Yurdakul (2010), Psillaki et al. (2010), Gutiérrez-Nieto et al. (2016)	
ABS	Burak Emel et al. (2003)	
short-term loans/ current liabilities ratio	Yurdakula and Tansel Iç (2004), Burak Emel et al. (2003)	
Credit history	Che et al. (2010), Gutiérrez-Nieto et al. (2016)	
current liabilities to net sales ratio	Tomić-Plazibat et al. (2006), Yurdakula and Tansel Iç (2004), Burak Emel et al. (2003)	
short-term loans/operational income	Che et al. (2010)	

methods usually assign the same weight to the ranking results of different MADM methods (Wang et al., 2016), or determine the weights based on the correlation of ranks, instead of scores (Varmazyar et al., 2016). However, considering ranks as the basis of the aggregation may reduce the accuracy of the final results, because the ranks are based on an ordinal scale which does not reveal the difference between alternatives (De Keyser and Peeters, 1996). Thus, it is necessary to utilize scores instead of ranks to increase the accuracy of aggregation. In this regard, to overcome the flaws in theory of dominance and obtain the final rankings, Barak and Heidary Dahooei (2018) used CCSD weighting for improving Fuzzy MULTIMOORA method. Due to the capability and robustness of the proposed method in overcoming the mentioned drawbacks in combination of different MADM methods, this approach is used to integrate the results.

5. Case illustration

The provision of credit facilities to the companies and people is one of the primary tasks of every bank. In this regard, one of the fundamental decisions banks and funding institutions face is lending money to a customer. Financial and credit institutions must be able to distinguish between punctual and non-punctual applicants. This ability is limited to the available data (Kozeny, 2015). These data are usually obtained from the request records, customer demographics, and past borrowing and repayment records (Xia et al., 2017).

In this study, the credit performance of 21 applicants in the Beekeeping Industry Funding Institute (BIFI) in Tehran, Iran, is evaluated from 2014 to 2017. This funding institute provides financial facilities and loans for beekeeping cooperative firms to develop their operations and fields. BIFI keeps all of the payment and capital-related records for each of these cooperative firms and investigates these data to decide to grant the facilities to an applicant firm. The credit performance of the selected companies is evaluated using the proposed methodology in Fig. 1.

5.1. Criteria weight calculation

Considering the importance of the credit risk, one of the challenges in financial institutions is that before granting facilities, the probability of failure and risk to repay from applicants will be evaluated to choose a group that is able to pay its debts. This could be done by a comprehensive, structured, and appropriate criteria selection (Bahabadi and Mohammadi, 2016). So it is very crucial to provide a model based on indicators and effective parameters to categorizes the credit applicants and reduce the risk of non-repayment of loans (Bahabadi and Mohammadi, 2016). various criteria, including economic, financial, and technical indicators, should be considered to develop a comprehensive credit evaluation framework (Yurdakul and Tansel I'c, 2004). The selected ratios should cover different aspects of corporate financial status (Tomić-Plazibat et al., 2006).

Altman (1968) introduced the Z score model applying the most important financial ratios of an organization as criteria or indicator of credit performance evaluation. Subsequently, Burak Emel et al. (2003) have used liquidity, activity, financial structure, profitability, growth, and capital flow to evaluate the credit performance of 82 industrial and manufacturing companies in Turkey. With a comprehensive literature review, it is obvious that there are 3 major categories for credit evaluation criteria (Yurdakul and Tansel I'c, 2004; Gutiérrez-Nieto et al., 2016; Tomić-Plazibat et al., 2006):

- Operation and profitability,
- Capital and long-term solvency,
- Short-term liquidity.

The financial ratios related to these categories can be divided into input and output categories which are represented in Table 4.

Due to the importance of criteria customization, a fuzzy Delphi approach is used to survey experts committee's opinion. Considering the applied criteria in previous studies, the frequency of them, the experts' opinion and the accessibility or availability of data, the following ratios are chosen for the credit evaluation of DMUs (applicant firms):

- Outputs (Positive criteria): pre-tax income/total capital ratio($\boldsymbol{y}_1$), net income/net sales ratio($\boldsymbol{y}_2$), working capital/total capital ratio($\boldsymbol{y}_3$).
- Inputs (Negative criteria): current liabilities to net sales ratio($\mathbf{x}_1$), short-term bank loans/current liabilities ratio($\mathbf{x}_2$), total liabilities/total assets ratio($\mathbf{x}_3$).

After determining the credit performance evaluation criteria and gathering the data for 21 selected beekeeping firms in the considered time horizon, the dynamic CSW method is applied to determine the weights of the six identified criteria. The optimal weights

Table 5
Final weights of criteria.

Input variables			Output variables		
v_1	v_2	v_3	u_1	u_2	u_3
0.229	0.029	0.229	0.171	0.171	0.171

Table 6
Means and Variances of data.

DMU	$\bar{x}_{i1}$	$\bar{x}_{i2}$	$\bar{x}_{i3}$	$\bar{y}_{i1}$	$\bar{y}_{i2}$	$\bar{y}_{i3}$	σ_1	σ_2	σ_3	δ_1	δ_2	δ_3
1	0.0009	0.7030	0.0194	0.0128	0.0151	0.0126	0.0001	0.1556	0.0013	0.0012	0.0000	0.0011
2	0.0007	0.7037	0.0215	0.0131	0.0154	0.0168	0.0000	0.1559	0.0020	0.0001	0.0001	0.0001
3	0.0014	0.7067	0.0165	0.0128	0.0148	0.0077	0.0002	0.1550	0.0018	0.0001	0.0000	0.0008
4	0.0009	0.7226	0.0270	0.0126	0.0148	0.0155	0.0001	0.1494	0.0014	0.0000	0.0000	0.0014
5	0.0010	0.8065	0.0173	0.0127	0.0150	0.0098	0.0001	0.1154	0.0017	0.0000	0.0000	0.0008
6	0.0008	0.9120	0.0152	0.0125	0.0148	0.0038	0.0000	0.0966	0.0020	0.0000	0.0000	0.0004
7	0.0012	0.7877	0.0201	0.0128	0.0155	0.0143	0.0001	0.1347	0.0015	0.0000	0.0002	0.0009
8	0.0009	0.9229	0.0284	0.0087	0.0099	0.0099	0.0001	0.0700	0.0017	0.0012	0.0000	0.0014
9	0.0009	0.7028	0.0169	0.0128	0.0152	0.0088	0.0000	0.1557	0.0018	0.0001	0.0001	0.0008
10	0.0007	0.7037	0.0199	0.0127	0.0149	0.0148	0.0000	0.1559	0.0018	0.0000	0.0000	0.0004
11	0.0014	0.7322	0.0265	0.0122	0.0146	0.0182	0.0002	0.1490	0.0002	0.0001	0.0001	0.0010
12	0.0008	0.7157	0.0224	0.0126	0.0148	0.0166	0.0001	0.1543	0.0013	0.0001	0.0001	0.0008
13	0.0007	0.9775	0.0173	0.0130	0.0153	0.0103	0.0000	0.1252	0.0021	0.0000	0.0000	0.0000
14	0.0008	3.9287	0.0613	0.0128	0.0152	0.0151	0.0000	0.8770	0.0123	0.0000	0.0000	0.0014
15	0.0011	0.7293	0.0212	0.0128	0.0153	0.0159	0.0001	0.1509	0.0015	0.0000	0.0000	0.0007
16	0.0009	1.8809	0.0169	0.0125	0.0148	0.0071	0.0000	0.2366	0.0018	0.0000	0.0000	0.0009
17	0.0009	0.7625	0.0192	0.0127	0.0152	0.0191	0.0001	0.1547	0.0014	0.0000	0.0001	0.0013
18	0.0008	0.7589	0.0170	0.0130	0.0152	0.0148	0.0000	0.1419	0.0015	0.0000	0.0000	0.0003
19	0.0011	0.7037	0.0212	0.0125	0.0148	0.0104	0.0001	0.1559	0.0000	0.0000	0.0000	0.0017
20	0.0014	0.7083	0.0168	0.0124	0.0136	0.0083	0.0002	0.1556	0.0018	0.0000	0.0005	0.0010
21	0.0005	0.4148	0.0135	0.0155	0.0158	0.0207	0.0000	0.0913	0.0016	0.0006	0.0001	0.0010

Table 7
Interval grey decision making matrix.

DMU	$\underline{x}_1$	$\overline{x}_1$	$\underline{x}_2$	$\overline{x}_2$	$\underline{x}_3$	$\overline{x}_3$	$\underline{y}_1$	$\overline{y}_1$	$\underline{y}_2$	$\overline{y}_2$	$\underline{y}_3$	$\overline{y}_3$
1	0.0013	0.0006	1.3989	0.0071	0.0252	0.0136	0.0176	0.0075	0.0151	0.0150	0.0176	0.0075
2	0.0007	0.0007	1.4009	0.0066	0.0305	0.0126	0.0173	0.0163	0.0158	0.0151	0.0173	0.0163
3	0.0025	0.0003	1.3999	0.0135	0.0246	0.0083	0.0111	0.0043	0.0148	0.0148	0.0111	0.0043
4	0.0012	0.0006	1.3909	0.0543	0.0330	0.0209	0.0218	0.0092	0.0148	0.0148	0.0218	0.0092
5	0.0014	0.0007	1.3226	0.2905	0.0252	0.0095	0.0133	0.0063	0.0151	0.0148	0.0133	0.0063
6	0.0009	0.0007	1.3439	0.4801	0.0243	0.0062	0.0056	0.0021	0.0148	0.0148	0.0056	0.0021
7	0.0017	0.0006	1.3902	0.1852	0.0269	0.0133	0.0183	0.0103	0.0163	0.0148	0.0183	0.0103
8	0.0013	0.0006	1.2358	0.6100	0.0359	0.0209	0.0159	0.0039	0.0099	0.0099	0.0159	0.0039
9	0.0011	0.0006	1.3990	0.0066	0.0250	0.0089	0.0125	0.0052	0.0159	0.0146	0.0125	0.0052
10	0.0007	0.0007	1.4009	0.0066	0.0280	0.0119	0.0165	0.0131	0.0150	0.0149	0.0165	0.0131
11	0.0023	0.0004	1.3985	0.0658	0.0273	0.0257	0.0227	0.0138	0.0151	0.0140	0.0227	0.0138
12	0.0010	0.0005	1.4056	0.0259	0.0280	0.0167	0.0202	0.0131	0.0152	0.0144	0.0202	0.0131
13	0.0007	0.0007	1.5375	0.4175	0.0267	0.0078	0.0103	0.0103	0.0153	0.0153	0.0103	0.0103
14	0.0009	0.0007	7.8509	0.0066	0.1164	0.0062	0.0213	0.0089	0.0153	0.0150	0.0213	0.0089
15	0.0015	0.0007	1.4041	0.0544	0.0280	0.0144	0.0188	0.0129	0.0153	0.0152	0.0188	0.0129
16	0.0010	0.0007	2.9389	0.8230	0.0248	0.0090	0.0113	0.0029	0.0148	0.0148	0.0113	0.0029
17	0.0011	0.0007	1.4542	0.0708	0.0255	0.0129	0.0250	0.0132	0.0155	0.0149	0.0250	0.0132
18	0.0008	0.0008	1.3937	0.1241	0.0238	0.0102	0.0160	0.0136	0.0153	0.0151	0.0160	0.0136
19	0.0015	0.0007	1.4009	0.0066	0.0213	0.0211	0.0182	0.0026	0.0148	0.0148	0.0182	0.0026
20	0.0025	0.0004	1.4043	0.0123	0.0248	0.0087	0.0128	0.0039	0.0157	0.0115	0.0128	0.0039
21	0.0007	0.0003	0.8230	0.0066	0.0209	0.0062	0.0250	0.0163	0.0163	0.0153	0.0250	0.0163

of all criteria (C1-C6) are obtained by formulating and solving the model presented in Eq. (2). The results of model (2) for all criteria are represented in Table 5.

5.2. Forming the interval decision making matrix using Chebyshev theory (Phase 2)

According to the second step of the proposed method, "*Chebyshev inequality bounds*" is used to construct the interval decision matrix. To this aim, the means and variances of data in the considered time period of 2014–2017 are calculated, which are represented in Table 6. Considering the 95% confidence level, $k = 1/\sqrt{0.05} = 4.472$. Using Eq. (3), the confidence intervals of $(\mu - k\sigma, \mu + k\sigma)$ for each criterion of each applicant (DMU) are calculated and represented in Table 7.

5.3. Ranking the DMUs using interval grey MADM methods (Phase 3)

According to the third step of the proposed algorithm, different interval methods can be used in this step. In this study, five different interval grey MADM methods, including ARARS-G, COPRAS-G, TOPSIS-G, VIKOR-G and SAW-G, are used for ranking the 21 beekeeping firms. The main reason to use these sets of methods is that according to Hwang and Yoon (1981), SAW and ARAS methods belong to scoring methods while TOPSIS, VIKOR, and COPRAS belong to compromising methods. This variety of methods can

- Normalization:

$$\tilde{x}'_{ij} = \frac{(1/\tilde{x}_{ij})}{\sum_{i=0}^{m}(1/\tilde{x}_{ij})}, \tilde{y}'_{ij} = \frac{\tilde{y}_{ij}}{\sum_{i=0}^{m}\tilde{y}_{ij}}$$

- Alternative score determination:

$$\tilde{S}_i = \sum_{j=1}^{3} v_j\tilde{x}'_{ij} + \sum_{r=1}^{3} u_r\tilde{y}'_{ij} = [\underline{s}_i, \overline{s}_i], i = 0, 1, 2, \ldots, m$$

- Using center-of-area method for transforming evaluations:

$$S_i = \frac{1}{2}(\underline{s}_i + \overline{s}_i), i = 0, 1, 2, \ldots, m$$

- Calculate utility degree of alternatives: $K_i = S_i/S_0, i = 1, 2, \ldots, m$

Fig. 2. ARAS-G algorithm.

secure the robustness of the results, considering the Pareto-optimality of MADM problems solution.

Additive Ratio Assessment (ARAS) introduced by Zavadskas and Turskis (2010), according to the theory that states that the accurate understanding of the world complex phenomena is possible through simple relative comparisons (Büyüközkan and Göçer, 2018; Heidary Dahooie et al., 2019a, 2019b; Liao et al., 2016). In this method, an ideal alternative is firstly created and added to the decision matrix. Then the utility of each alternative is determined relative to the ideal solution. Finally, the alternative with the highest utility is chosen as the best alternative. Turskis and Zavadskas (2010) introduced the interval grey version of this method. Considering the aggregated decision matrix $D = [x_1, x_2, x_3, y_1, y_2, y_3]$ and the CSW-DEA based weighting vector $w = [v_1, v_2, v_3, u_1, u_2, u_3]$, the ARAS-G method started with determining an ideal alternative $A_0 = [x_{0j}, y_{0j}]$, where $x_{0j} = \min_i \{x_{ij}\}$, $y_{0j} = \max_i \{y_{ij}\}$. The steps of ARAS-G are illustrated in Fig. 2.

COmplex PRoportional Assessment (COPRAS) is another MADM method, which identifies the best alternative among a set of alternatives by determining a solution based on the ratio to the ideal and with the ideal-worst solution (Zavadskas et al., 1994). Because of some advantages (e.g. to consider both the ideal and the ideal-worst solutions in the same formula, to provide little and simple calculations, and to allow the decision maker reach a conclusion in a shorter time) COPRAS is used to solve different decision-making problems (Razavi Hajiagha et al., 2013; Şahin, 2019). The interval grey COPRAS technique is introduced by Zavadskas et al. (2009). The implementation steps of this method are illustrated in Fig. 3.

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is one of the well-known and widely used MADM techniques (Jahanshahloo et al., 2006). Among numerous MADM methods TOPSIS continues to work satisfactorily in diverse application areas and so has received much interest from researchers and practitioners (Behzadian et al., 2012; Salih et al., 2019). The selected solution is the alternative that simultaneously is near to the positive ideal solution (PIS) and far from the negative ideal solution (NIS) (Wang and Lee, 2009). The calculation method of interval grey TOPSIS is taken from Jahanshahloo et al. (2006) as illustrated in Fig. 4.

- Normalization:

$$\tilde{x}'_{ij} = \left[\frac{2\underline{x}_{ij}}{\sum_{i=1}^{m}(\underline{x}_{ij}+\overline{x}_{ij})}, \frac{2\overline{x}_{ij}}{\sum_{i=1}^{m}(\underline{x}_{ij}+\overline{x}_{ij})}\right], \tilde{y}'_{ij} = \left[\frac{2\underline{y}_{ij}}{\sum_{i=1}^{m}(\underline{y}_{ij}+\overline{y}_{ij})}, \frac{2\overline{y}_{ij}}{\sum_{i=1}^{m}(\underline{y}_{ij}+\overline{y}_{ij})}\right]$$

- Calculate the weighted normalized matrix $\widetilde{V} = [\widetilde{vx}_i, \widetilde{vy}_r]$

$$\widetilde{vx}_{ij} = v_j\tilde{x}'_{ij}, \widetilde{vy}_{ij} = u_i\tilde{y}'_{ij}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, k + s$$

- Calculate the sum $P_i = \frac{1}{2}\sum_{j=1}^{r}\left(\underline{vy}_{ij} + \overline{vy}_{ij}\right), i = 1, 2, \ldots, m$
- Calculate the sum $R_i = \frac{1}{2}\sum_{j=1}^{k}\left(\underline{vx}_{ij} + \overline{vx}_{ij}\right), i = 1, 2, \ldots, m$
- Determine the minimum value of $R_{min} = \min_i\{R_i\}$
- Calculating the relative weight of each alternative $\mathbf{Q_i}$:

$$Q_i = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} \frac{1}{R_i}}$$

Fig. 3. COPRAS-G algorithm.

Churchman and Ackoff (1954) proposed the simple additive weighting (SAW) for a portfolio selection problem. Because of its simplicity, the SAW method is the most popular and widely used MADM method (Heidary Dahooie et al., 2020). The SAW-G method proposed by Zavadskas et al. (2010) is used to rank 21 DMUs. The calculation method of SAW-G is illustrated in Fig. 5.

The VIKOR method also developed as a MADM method to solve decision problems with non-commensurable and conflicting criteria (Opricovic and Tzeng, 2007) and continues to be applied satisfactorily across different application areas (Gul et al., 2016). This method focuses on ranking and selecting from a set of alternatives, and determines compromised solutions for a problem with conflicting criteria, which can help the decision makers to reach a final decision (Sayadi et al., 2009). The final scores (Q_j) are determined based on the VIKOR-G method, which is explained in Fig. 6.

Table 8 illustrates the results of applicants' ranking by different methods.

5.4. Compounding the results (Phase 4)

Wang and Luo (2010) proposed the CCSD as a new method for weighting criteria, combining the correlation coefficient and the standard deviation of the criteria. Comparing other objective weighting methods, CCSD has lots of advantages including no need for a special normalization, more inclusive and reliable weights than the entropy and SD methods, and having a comprehensible mechanism than the CRITIC method are part of the superiorities of the CCSD method. Heidary Dahooie et al. (2019a), Heidary Dahooie et al. (2019b) described the steps of this method.

In this step, the CCSD method is used on different interval grey methods results, represented in table 8, in order to integrate them. The weight of each method is derived using CCSD which is presented in Table 9.

Determining the weights, the secondary decision matrix (consisting of five method scores) is normalized. The following equations are used for normalization.

$$\boldsymbol{z_{ij}} = \frac{\boldsymbol{x_{ij}} - \boldsymbol{x_j^{min}}}{\boldsymbol{x_j^{max}} - \boldsymbol{x_j^{min}}}, \boldsymbol{i} = 1, \cdots, \boldsymbol{n}; \boldsymbol{j} \in \boldsymbol{\Omega_b} \tag{4}$$

$$\boldsymbol{z_{ij}} = \frac{\boldsymbol{x_j^{max}} - \boldsymbol{x_{ij}}}{\boldsymbol{x_j^{max}} - \boldsymbol{x_j^{min}}}, \boldsymbol{i} = 1, \cdots, \boldsymbol{n}; \boldsymbol{j} \in \boldsymbol{\Omega_c} \tag{5}$$

In this equation, $x_j^{min} = \min_{1 \le i \le n}\{x_{ij}\}, x_j^{max} = \max_{1 \le i \le n}\{x_{ij}\}$ and Ω_b and Ω_c are the set of positive and negative criteria indices, respectively. Table 10 illustrates the secondary normalized decision matrix.

Finally, the aggregated performance and the final rank of alternatives are calculated using the following equation.

$$\ddot{S}_i = \sum_{j=1}^{5} \ddot{z}_{ij} \cdot \ddot{w}_j \tag{6}$$

where $\ddot{w}_j$ is the weight of the jth method in the final performance; and $\ddot{z}_{ij}$ is the normalized value of the ith applicant in the jth method. The alternatives are ranked based on descending values of $\ddot{S}_i$. The final score and the rank of each alternative are represented in Table 11.

- Normalization:

$$\widetilde{x}'_{ij}=\left[\frac{\underline{x}_{ij}}{\sqrt{\sum_{i=1}^{m}\underline{x}_{ij}^{2}+\overline{x}_{ij}^{2}}},\frac{\overline{x}_{ij}}{\sqrt{\sum_{i=1}^{m}\underline{x}_{ij}^{2}+\overline{x}_{ij}^{2}}}\right],\widetilde{y}'_{ij}=\left[\frac{\underline{y}_{ij}}{\sqrt{\sum_{i=1}^{m}\underline{y}_{ij}^{2}+\overline{y}_{ij}^{2}}},\frac{\overline{y}_{ij}}{\sum_{i=1}^{m}\left(\underline{y}_{ij}+\overline{y}_{ij}\right)}\right]$$

- Calculate the weighted normalized matrix $\widetilde{V}=[\widetilde{vx}_i,\widetilde{vy}_r]$

$$\widetilde{vx}_{ij}=v_j\widetilde{x}'_{ij},\widetilde{vy}_{ij}=u_i\widetilde{y}'_{ij},i=1,2,\ldots,m,j=1,2,\ldots,k+s$$

- Determine the positive ideal (PI) and negative ideal (NI) solutions

$$PI=(x_1^+,x_2^+,\ldots,x_k^+,y_1^+,y_2^+,\ldots,y_s^+)=\left\{\left(\min_i \underline{vx}_{ij}\,\middle|\,j=1,2,\ldots,k\right),\left(\max_i \overline{vy}_{ij}\,\middle|\,j=1,2,\ldots,s\right)\right\}$$

$$NI=(x_1^-,x_2^-,\ldots,x_k^-,y_1^-,y_2^-,\ldots,y_s^-)=\left\{\left(\max_i \overline{vx}_{ij}\,\middle|\,j=1,2,\ldots,k\right),\left(\min_i \underline{vy}_{ij}\,\middle|\,j=1,2,\ldots,s\right)\right\}$$

- Calculate the distance of each alternative from PI

$$d_i^+=\sqrt{\sum_{j=1}^{k}\left(\overline{vx}_{ij}-x_j^+\right)^2+\sum_{j=1}^{k}\left(\underline{vy}_{ij}-y_j^+\right)^2},i=1,2,\ldots,m$$

- Calculate the distance of each alternative from NI

$$d_i^-=\sqrt{\sum_{j=1}^{k}\left(\underline{vx}_{ij}-x_j^-\right)^2+\sum_{j=1}^{k}\left(\overline{vy}_{ij}-y_j^-\right)^2},i=1,2,\ldots,m$$

- Calculating the closeness coefficient of each alternative $\mathbf{CC_i}$:

$$CC_i=\frac{d_i^-}{d_i^-+d_i^+},i=1,2,\ldots,m$$

Fig. 4. TOPSIS-G algorithm.

- Normalization:

$$\widetilde{x}'_{ij}=\left[\underline{x}'_{ij},\overline{x}'_{ij}\right]=\left[\frac{\min_i \underline{x}_{ij}}{\overline{x}_{ij}},\frac{\min_i \underline{x}_{ij}}{\underline{x}_{ij}}\right],\widetilde{y}'_{ij}=\left[\underline{y}'_{ij},\overline{y}'_{ij}\right]=\left[\frac{\underline{y}_{ij}}{\max_i \overline{y}_{ij}},\frac{\overline{y}_{ij}}{\max_i \overline{y}_{ij}}\right]$$

- Calculate the optimality degree of each alternative:

$$L_i=\frac{1}{k+s}\left[\sum_{j=1}^{k}v_j\left(\frac{\underline{x}'_{ij}+\overline{x}'_{ij}}{2}\right)+\sum_{j=1}^{s}u_j\left(\frac{\underline{y}'_{ij}+\overline{y}'_{ij}}{2}\right)\right]$$

Fig. 5. SAW-G algorithm.

5.5. Comparison and analysis

In this section, a comparison is made between the individual methods with the results obtained from CCSD. First, Fig. 7 illustrates the correlation among the different methods scores. According to this figure, it is clear that minimum correlation among different methods is 70%. Also, it can be seen that the CCSD result illustrates a relatively high consistency with other methods that can enhance its acceptancy.

Also, Fig. 8 demonstrates the ranking of alternatives in different methods. Here again, the CCSD aggregated rank illustrates a good consistency with different methods.

As the final ranking shows, DMU_U, DMU_B and DMU_R are the three beekeeping firms with the highest priority regarding their credit performance. In order to summarize the performance of the proposed method and measuring the similarity of the rankings obtained from the proposed method with the rankings of other methods, the Spearman rank correlation coefficient, Eq. (7) is used.

$$\boldsymbol{r_s}=1-\frac{\sum_{i=1}^{\boldsymbol{n}}\boldsymbol{d_i^2}}{\boldsymbol{n}^3-\boldsymbol{n}}\tag{7}$$

where d_i is the difference between the ranks of alternative i in the proposed method and the other methods. Also, n denotes the number of alternatives. The values of the Spearman rank correlation coefficient are given in Table 12.

As can be seen, the proposed method is highly correlated with five used method.

6. Conclusion

Credit performance of loan applicant firms plays a significant role in the financial and economic development of each society. One of the key elements of this development is to ensure the accurate and efficient evaluation of the credit performance of these loan applicants. Assessing the credit performance of these loan applicant firms can help the financial institutes including banks and funding institutes, to make appropriate decision about whether or not to grant financial facilities to an applicant.

In this regard, various approaches are developed for evaluation of credit performance. Among these approaches, MADM and DEA have received great attention, due to the shortcomings of statistical and data-based methods (such as neural networks or SVM) including: requirement of large amount of data, complicated and costly calculations considering several evaluation criteria which some of them may not be qualitatively assessable and also different importance degree of each criterion.

As described before, developed practices in MADM and DEA methods also face some limitations which are tried to be addressed in this paper. Thus, a Dynamic MADM framework proposed

- Determine the positive ideal (PI) and negative ideal (NI) solutions:

$$PI = (x_1^+, x_2^+, \dots, x_k^+, y_1^+, y_2^+, \dots, y_s^+) = \left\{ \left(\min_i \underline{x}_{ij} \,\middle|\, j = 1, 2, \dots, k \right), \left(\max_i \overline{y}_{ij} \,\middle|\, j = 1, 2, \dots, s \right) \right\}$$

$$NI = (x_1^-, x_2^-, \dots, x_k^-, y_1^-, y_2^-, \dots, y_s^-) = \left\{ \left(\max_i \overline{x}_{ij} \,\middle|\, j = 1, 2, \dots, k \right), \left(\min_i \underline{y}_{ij} \,\middle|\, j = 1, 2, \dots, s \right) \right\}$$

- Compute $[\underline{S}_i, \overline{S}_i]$ and $[\underline{R}_i, \overline{R}_i]$ intervals for each alternative as below

$$\underline{S}_i = \sum_{j=1}^{k} v_j \left(\frac{\underline{x}_{ij} - x_j^+}{x_j^- - x_j^+} \right) + \sum_{j=1}^{k} u_j \left(\frac{y_j^+ - \overline{y}_{ij}}{y_j^+ - y_j^-} \right), i = 1, 2, \dots, m$$

$$\overline{S}_i = \sum_{j=1}^{k} v_j \left(\frac{\overline{x}_{ij} - x_j^+}{x_j^- - x_j^+} \right) + \sum_{j=1}^{k} u_j \left(\frac{y_j^+ - \underline{y}_{ij}}{y_j^+ - y_j^-} \right), i = 1, 2, \dots, m$$

$$\underline{R}_i = Max \left\{ v_j \left(\frac{\underline{x}_{ij} - x_j^+}{x_j^- - x_j^+} \right) \middle| j = 1, 2, \dots, k, u_j \left(\frac{y_j^+ - \overline{y}_{ij}}{y_j^+ - y_j^-} \right) \middle| j = 1, 2, \dots, k \right\}, i = 1, 2, \dots, m$$

$$\overline{R}_i = Max \left\{ v_j \left(\frac{\overline{x}_{ij} - x_j^+}{x_j^- - x_j^+} \right) \middle| j = 1,2, \dots, k, u_j \left(\frac{y_j^+ - \underline{y}_{ij}}{y_j^+ - y_j^-} \right) \middle| j = 1,2, \dots, k \right\}, i = 1,2, \dots, m$$

- Compute the interval $\mathbf{Q_i} = [\underline{Q}_i, \overline{Q}_i,]$; i = 1,2,. . .,m, by these relations:

$$\underline{Q}_i = v \frac{(\underline{S}_i - S^*)}{(S^- - S^*)} + (1 - v) \frac{(\underline{R}_i - R^*)}{(R^- - R^*)}$$

$$\overline{Q}_i = v \frac{(\overline{S}_i - S^*)}{(S^- - S^*)} + (1 - v) \frac{(\overline{R}_i - R^*)}{(R^- - R^*)}$$

Where $S^* = \min_i \underline{S}_i$, $S^- = \max_i \overline{S}_i$, $R^* = \min_i \underline{R}_i$, $R^- = \max_i \overline{R}_i$, and $v \in [0, 1]$.

Fig. 6. COPRAS-G algorithm.

Table 8
Credit applicants' evaluation results.

	ARAS		SAW-G		COPRAS-G		TOPSIS-G		VIKOR-G	
DMUs	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
DMU_A	0.813	9	0.723	9	0.131	9	0.773	9	0.374	12
DMU_B	0.882	2	0.784	2	0.141	3	0.816	3	0.061	2
DMU_C	0.712	19	0.633	19	0.106	18	0.689	20	0.386	19
DMU_D	0.810	11	0.720	11	0.125	12	0.757	13	0.292	9
DMU_E	0.775	13	0.689	13	0.124	13	0.761	12	0.365	11
DMU_F	0.745	17	0.662	17	0.127	10	0.752	15	0.492	16
DMU_G	0.811	10	0.721	10	0.123	14	0.754	14	0.245	10
DMU_H	0.557	21	0.495	21	0.105	20	0.704	17	0.729	21
DMU_I	0.799	12	0.710	12	0.131	8	0.775	8	0.400	13
DMU_J	0.849	6	0.755	6	0.141	4	0.813	4	0.164	4
DMU_K	0.769	14	0.683	14	0.116	16	0.701	18	0.179	14
DMU_L	0.850	5	0.755	5	0.137	6	0.803	6	0.165	6
DMU_M	0.830	7	0.738	7	0.136	7	0.795	7	0.225	7
DMU_N	0.743	18	0.661	18	0.084	21	0.536	21	0.271	18
DMU_O	0.821	8	0.730	8	0.126	11	0.767	10	0.160	8
DMU_P	0.762	15	0.677	15	0.112	17	0.762	11	0.469	15
DMU_Q	0.871	3	0.774	3	0.141	5	0.808	5	0.160	5
DMU_R	0.857	4	0.762	4	0.143	2	0.821	2	0.140	3
DMU_S	0.759	16	0.674	16	0.123	15	0.741	16	0.501	17
DMU_T	0.676	20	0.601	20	0.106	19	0.692	19	0.492	20
DMU_U	1.000	1	0.889	1	0.188	1	0.881	1	0.000	1

Table 9
Weight of each method using CCSD.

Method	ARAS	*SAW*	*COPRAS*	*TOPSIS*	VIKOR
Weight	0.1623	0.1628	0.1699	0.2682	0.2368

containing three main phases (including; set up an evaluation committee and determining the credit performance evaluation criteria, calculating customer credit scores using a new dynamic multi-attribute decision-making approach, combining the results and sensitivity analysis) and the pitfalls and limitations are resolved through the strength and characteristics of different MADM and DEA techniques. The proposed framework results in the following benefits for decision makers:

- Considering performance data related to different time intervals rather than considering only one period of time data (MADM as the general approach)

Table 10
The normalized secondary decision matrix.

DMUs	ARAS-G	SAW – G	COPRAS – G	TOPSIS – G	VIKOR-G
DMU_A	0.579	0.579	0.449774	0.686874	0.475946
DMU_B	0.734384	0.734384	0.54597	0.81111	0.938292
DMU_C	0.349558	0.349558	0.211221	0.442646	0.201235
DMU_D	0.571414	0.571414	0.398775	0.641323	0.592673
DMU_E	0.492722	0.492722	0.387335	0.653622	0.487098
DMU_F	0.424881	0.424881	0.409519	0.626903	0.343905
DMU_G	0.573925	0.573925	0.375579	0.631615	0.558839
DMU_H	0	0	0.208286	0.487318	0
DMU_I	0.546373	0.546373	0.449795	0.693528	0.454926
DMU_J	0.659463	0.659463	0.545893	0.802638	0.802448
DMU_K	0.477938	0.477938	0.312262	0.477084	0.426245
DMU_L	0.660736	0.660736	0.505705	0.774108	0.770102
DMU_M	0.617465	0.617465	0.495465	0.752126	0.715716
DMU_N	0.420805	0.420805	0	0	0.279767
DMU_O	0.596384	0.596384	0.400089	0.670894	0.682832
DMU_P	0.462648	0.462648	0.273041	0.654837	0.365725
DMU_Q	0.708711	0.708711	0.543167	0.789069	0.781093
DMU_R	0.677559	0.677559	0.570586	0.826492	0.831093
DMU_S	0.455524	0.455524	0.37556	0.59528	0.315324
DMU_T	0.268547	0.268547	0.210637	0.452631	0.087923
DMU_U	1	1	1	1	1

Table 11
DMU scores and final ranks using CCSD method.

DMUs	$\ddot{S}_i$	Rank	DMUs	$\ddot{S}_i$	Rank
DMU_A	0.561573218	10	DMU_L	0.69070053	6
DMU_B	0.771235903	2	DMU_M	0.656119353	7
DMU_C	0.315897816	18	DMU_N	0.203052382	20
DMU_D	0.565866398	9	DMU_O	0.603487781	8
DMU_E	0.516638354	13	DMU_P	0.459027596	14
DMU_F	0.457278254	15	DMU_Q	0.719276963	4
DMU_G	0.552126339	11	DMU_R	0.735685035	3
DMU_H	0.166086622	21	DMU_S	0.44622122	16
DMU_I	0.547776608	12	DMU_T	0.265307587	19
DMU_J	0.712426153	5	DMU_U	1	1
DMU_K	0.437319974	17			

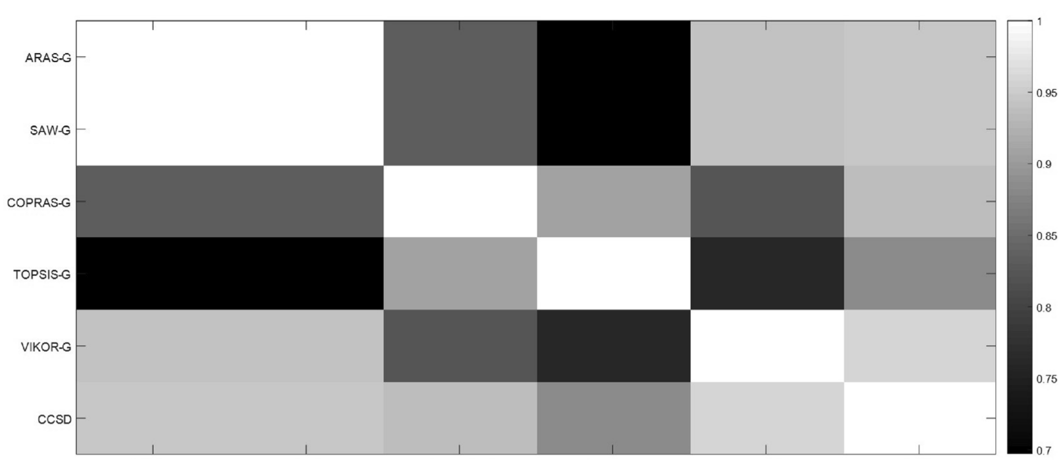

Fig. 7. Scores correlation among aggregated CCSD and different methods.

- Calculating the criteria weights based on data (rather than experts' opinions) using DEA as a robust objective method (applying DEA model with CSW approach)
- Integrating the performance scores of DMUs according to the criteria, taking into account data changes over time (using Chebyshev's theory and gray number decision matrix).
- Increasing the robustness of multi-attribute decision-making by aggregating the results of 5 different MADM methods so that the shortcomings of previous aggregation methods (such as considering the same weight for all methods and using the rank for the final comparison of DMUs) are eliminated (Using CCSD)

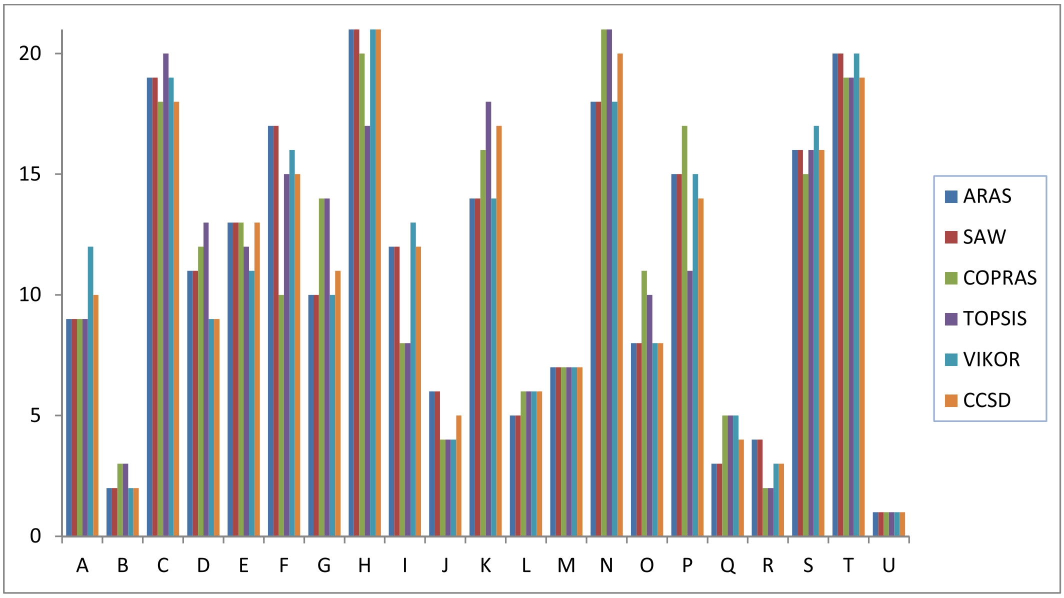

Fig. 8. Ranking obtained using different MADM methods and aggregated ranking results.

Table 12
Spearman rank correlation coefficient between the proposed method and MADM methods.

	ARAS	SAW	COPRAS	TOPSIS	VIKOR
CC	0.980519481	0.980519	0.944156	0.946753	0.980519

The developed approach is used in order to calculate the credit score of the beekeeping industry development fund's clients and to rank 21 firms of its clients over a certain period of time, and finally the robustness of results is demonstrated through sensitivity analysis.

Given that the subject of DMADM is still at the beginning of its research path, future researches could develop new approaches in this field. Calculating different weights in different time periods for ranking, considering the relation between criteria, as well as using fuzzy, IVIF or HF data which indicate the uncertainty in the decision making process can enhance the efficiency of this model in real-world problems.

CRediT authorship contribution statement

Jalil Heidary Dahooie: Methodology, Formal analysis. **Seyed Hossein Razavi Hajiagha:** Conceptualization, Validation. **Shima Farazmehr:** Project administration, Writing - original draft. **Edmundas Kazimieras Zavadskas:** Supervision, Writing - review & editing. **Jurgita Antucheviciene:** Investigation, Writing - review & editing.

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