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Ranking based on optimal points and win-loss-draw multi-criteria decision-making with application to supplier evaluation problem

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ABSTRACT

Supplier evaluation is a complex multi-criteria decision-making (MCDM) problem that deals with assessment of suppliers as the potential alternatives against various types of criteria. We consider the context where decision makers (DMs) have complete information about the suppliers and criteria. To address the needs of decision makers, a multi-criteria evaluation method named Ranking based on optimal points (RBOP) is developed in this paper. By imitating and simulating human decision-making behavioural patterns, the developed MCDM method selects the best alternative that is closer to what the DM desires. Furthermore, a novel subjective MCDM weighting methods called win-loss-draw (WLD) method is also developed, which is also based on human behavioural pattern. A real case study of domestic cheese brands is considered to apply the developed methods to select the best cheese supplier for an Iranian hypermarket. Compared to other MCDM methods, outputs of the RBOP method show some differences due to the impact of WLD method, which intensified divergence and optimal points during the decision-making process.

1. Introduction

Supplier evaluation is an important industrial problem in which different criteria are considered simultaneously to identify, assess, and deal with suppliers. It is a non-stop process of precisely investigating suppliers which includes qualified verification process. An appropriate supplier selection process can potentially reduce costs and provide high quality products (Gören, 2018; Negash, Kartika, Tseng, & Tan, 2020). To illustrate the importance of supplier selection, el Hiri, En-Nadi, and Chafi (2019) defined it as an essential activity for enhancing organizational efforts to maintain global market position. On the other hand, the importance of supply chain management (SCM) in food industry has been expanded both at the industrial and methodical aspects (Panchal, Jain, Cheikhrouhou, & Gurtner, 2017). Any Food SCM (FSC) is based on the activities or operations from production, distribution, and consumption to maintain safety and quality of different food products under efficient and effective circumstances (Blandon, Henson, & Cranfield, 2009). A FSC is characterized by specific factors like quality, safety and freshness in food products, which make the underlying SCM more complex and challenging to handle (Zhong, Xu, & Wang, 2017). Challenges faced in FSCs are at the intersection of several disciplines and go beyond traditional cost minimization approaches. Food companies deal with higher upstream and downstream uncertainties which are related to ever increasing product varieties, more demanding customers and highly interconnected distribution networks (Amorim, Curcio, Almada-Lobo, Barbosa-Póvoa, & Grossmann, 2016). In supplier selection problems, opinions of decision makers (DMs) always have some qualitative features, which cannot be efficiently and mathematically operable (Zakeri & Keramati, 2015). Selection of the best supplier is affected by different intangible and tangible criteria such as technical capability, service level, price, and quality (Azadnia, 2016). These criteria make the supplier selection process a complex decision making problem and classifies it as a multiple-criteria decision-making (MCDM) problem. In spite of the fact that each MCDM method has its unique mathematical modelling and solves problems within its unique philosophy, their algorithms are designed to find the best alternative through analysis of decision matrices and computation of criteria weights which usually carries out with DMs' interjection.

In this paper, we consider the case of eight dairy companies as cheese suppliers of a hypermarket, evaluated through ten criteria taking into account the previously investigated studies. In order to evaluate suppliers, a new crisp MCDM method called Ranking based on Optimal

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Points (RBOP) method is developed in this paper. Concerning to evaluation goals, most solo or integrated MCDM methods generally analyse performance of the suppliers against a set of pre-defined criteria and ignores the desire, expectations, and tendency of DMs. This ignorance emerges as a problem when DMs possess perfect information about the criteria and alternatives. Thus, DMs may manipulate outputs to make them closer to their mind-set. In particular, in the case of fast-moving consumer goods (FMCG) products, due to the frequent periodic orders, hypermarkets generally have complete information about famous brands to supply products. Ranking based on optimal points (RBOP) gives a different perspective of suppliers' evaluation as the method provides the best alternative closer to what the DMs desire.

The remainder of the paper is organized as follows: In the second section, previous studies related to the current work are reviewed and discussed. Section 3 presents a brief review on RBOP; In section four, RBOP with crisp numbers and also the win-loss-draw (WLD) method as a new MCDM weighting method are introduced. The fifth section is dedicated to the RBOP application to the cheese suppliers' evaluation problem. Section 6 addresses the comparison of the RBOP and WLD method with the state-of-the-art MCDM methods, and also the limitations of the new method. Finally, Section 7 concludes the paper and frames future research work.

2. Literature review

This section is divided into three sub sections entitled: MCDM methods and their application on the supplier evaluation and selection; MCDM application on the food supplier evaluation/selection; and the selection of the criteria, which investigates the criteria previously used in earlier studies of hypermarkets supplier evaluation and selection studies.

2.1. MCDM methods and their applications in supplier evaluation/selection

Every MCDM method utilizes distinctive policy to analyze decision matrices in order to rank alternatives. In general, philosophies of general MCDM methods for ranking can be categorized as outranking methods like ELimination Et Choix Traduisant la REalité (ELECTRE) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), compromise ranking such as grey relational analysis (GRA), (Zhang & Li, 2018), distance based such as Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and pairwise comparison-based methods like Analytic hierarchy process (AHP) and analytic network process (ANP). With a hierarchical structure, AHP is employed for assigning weights to criteria with consistency check of experts (Kumar, Padhi, & Sarkar, 2019). As a general form of AHP, ANP is developed to analyse problems with mutual dependencies of criteria (Tirkolaee, Mardani, Dashtian, Soltani, & Weber, 2020). Analogous to AHP, Best-Worst Method (BWM) is also based on pairwise comparisons between the best and worst criteria with the rest of criteria but requires fewer and less complex comparisons than AHP (Abdel-Basset, Mohamed, Zaied, Gamal, & Smarandache, 2020). PROMETHEE also follows pairwise comparisons with some notable advantages such as user friendliness and ability to provide both partial and complete rankings of alternatives (Wan, Zou, Zhong, & Dong, 2019). TOPSIS method works through alternative comparisons by identifying weight of each criterion, normalizing scores of each criterion, and finally calculating geometric distance between each alternative and ideal alternative (Javad & Darvishi, 2020). Similar to TOPSIS method, VIKOR method exploits the concept of positive and negative ideal solutions as ranking indices for MCDM problems (Opricovic & Tzeng, 2007; Wen, Chang, & Lai, 2020); and Decision Making Trial and Evaluation Laboratory (DEMATEL) has been acknowledged as a relatively effective and feasible method to prioritize criteria, considering causal interrelationship between various criteria (Chen, Ming, Zhou, & Chang, 2020). A description of the main MCDM methods used to solve supplier selection problems is listed in Table 1. The methods simply function though analysing decision-matrices and do not take into account desires and expectations of DMs, their impacts on setting goals and expectations from final products with complete/perfect information about decision-making goals, alternatives, and criteria. Consequently, in these situations, DMs unconsciously make ranking of alternatives and potentially desire to receive the closest results to what they desire, which is entirely against the conventional MCDM methods. Ho, Xu, and Dey (2010) reviewed 78 journal articles from 2000 to 2008 to answer the following questions: 1. which approaches are prevalently applied? 2. Which evaluating criteria are given more attention? 3. Is there any inadequacy of the approaches? Based on their findings, they concluded that individual approaches were slightly more popular than integrated approaches and data envelopment analysis (DEA), AHP, ANP and simple multi-attribute rating technique (SMART) methods emerged out as the most popular MCDM methods (Tables 2 and 3).

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Table 1
MCDM application in supplier selection problems where the star mark shows the combined model.

Method	Literature	Integrated/hybrid/combined method							Features of Decision Approach
		AHP	ANP	TOPSIS	COPRAS	VIKOR	DEMATEL	BWM	
AHP	Agrawal & Kant, 2020			*			*		Using a combined model of Fuzzy AHP, Fuzzy DEMATEL, and Fuzzy TOPSIS to select the best supplier.
	Yu, Zou, Shao, & Zhang, 2019			*					Developing a new integrated supplier selection approach including decision maker's risk attitude using the ANN, AHP and TOPSIS methods.
	Venkatesh, Zhang, Deakins, Luthra, & Mangla, 2019			*					In the article fuzzy AHP was used to compute the weights of the humanitarian supply partner selection criteria, and fuzzy TOPSIS has been employed and fuzzy in order to efficiently select the best supply partner for relief organizations.
	Fu, 2019								An integrated method of AHP, ARAS and MCGP has been developed in order to solve catering supplier selection's problem.
	Buriticá et al., 2019								Evaluation of 149 retail suppliers in Colombia evaluated by a proposed four-phase methodology diagnosis combining using K-means and multi-criteria fuzzification.
	Jain, Sangaiah, Sakhuja, Thoduka, & Aggarwal, 2018			*					A case study of the Indian automotive industry
	Li & Sun *et al.*, 2018			*					Proposed integrated approach of fuzzy AHP and TOPSIS
	Shakourloo, Kazemi, & Javad, 2016								Implemented by a group of experts including security professionals, management technicians, and workers, the fuzzy AHP is used to identify the appropriate supplier for providing each product.
ANP	Abdel-Basset, Chang, Gamal, & Smarandache, 2019					*			Using and integrated ANP and VIKOR under neutrosophic environment to evaluate the suppliers. ANP has been used to compute the weight of criteria.
	Sennaroglu & Akıcı, 2019								By providing ten criteria for evaluation of three suppliers of the main raw material requirement of a company in the chemical industry by using Fuzzy ANP.
	Danai, Hashemnia, Ahmadi, & Bazazzadeh, 2019								Fuzzy ANP has been employed to evaluate the suppliers of an Iranian company.
TOPSIS	Lei, Wei, Gao, Wu, & Wei, 2020								TOPSIS has been used as a platform to design an optimization model for deriving the weight information of the attribute.
	Rouyendegh, Yildizbasi, & Üstünyer, 2020								Intuitionistic Fuzzy TOPSIS method has been used to solve the green supplier selection in the case of a company located in Ankara.
	Memari, Dargi, Jokar, Ahmad, & Rahim, 2019								Sustainable supplier selection problem/An automotive spare parts manufacturer
	Mohammed, 2019								A seven-step integrated method of fuzzy TOPSIS and a developed multi-objective method as the possibilistic multi-objective optimization model (PMOOM) has been used in this article in order to evaluate the sustainable suppliers of livestock and meat packets by analyzing them against sixteen criterion.
	Abdel-Basset, Chang et al., 2019, Abdel-Basset, Saleh, Gamal, & Smarandache, 2019								Developed the advanced type of neutrosophic technique, called type 2 neutrosophic numbers, and a T2NN-TOPSIS strategy combining type 2 neutrosophic numbers and TOPSIS under group decision making as application of T2NN
	Li, Fang, & Song, 2019								a case study of sustainable photovoltaic modules supplier selection/ developing an extended TOPSIS
	Abdel-Basset, Mohamed, & Smarandache, 2018		*						A case study of a dairy company in Egypt
	Roshandel, Miri-Nargesi, & Hatami-Shirkouhi, 2013								They used a novel form of fuzzy TOPSIS called hierarchical fuzzy TOPSIS to evaluate the raw material suppliers of a producer of detergent powders located in Iran.
	Kilic, 2013								Through analyzing five criterion including quality, cost, delivery time, geographical location, and references, they developed a two-step combined method of fuzzy TOPSIS and the mixed integer linear programming (MILP) mode to select the best suppliers of an air filter company which located in Istanbul, Turkey.
COPRAS	Kumari & Mishra, 2020								Benefiting from intuitionistic fuzzy information, they used COPRAS to solve a green supplier selection problem.
	Qin & Liu, 2019							*	They represent the application of interval type-2 COPRAS based on an improved BWM method for emergency material supplier selection.
VIKOR	Fei, Deng, & Hu, 2019								Using Dempster–Shafer evidence theory (D-S theory), and DS-VIKOR to solve the supplier selection problem.

(*continued on next page*)

Table 1 (*continued*)

Method	Literature	Integrated/hybrid/combined method							Features of Decision Approach
		AHP	ANP	TOPSIS	COPRAS	VIKOR	DEMATEL	BWM	
	Sharaf, 2019								This paper proposed a novel flexible multi-attribute group decision-making method based on VIKOR using interval-valued fuzzy sets to solve the supplier selection problem.
DEMATEL	Kaya & Yet, 2019								They have proposed an integrated model of DEMATEL in the Bayesian Networks constructure to build probabilistic decision support models (by systematically exploiting expert knowledge) for solving a supplier selection problem in the case of a large automobile manufacturer in Turkey.
	Li, Diabat, & Lu, 2019								This study considers supplier selection with two different strategic perspectives, including lean and agile using DEMATEL to analyses the criteria.
BWM	Gan, Zhong, Liu, & Yang, 2019			*					By development of a hybrid method combining triangular fuzzy number, the best-worst method (BWM), and the modular TOPSIS in random environments for group decision-making (GMo-RTOPSIS) for evaluation/selection of the resilient supplier under supply chain environment.
	Yucesan, Mete, Serin, Celik, & Gul, 2019			*					They proposed a multi-phase MCDM model based on the BWM and the interval type-2 fuzzy TOPSIS for the green supplier selection of a plastic injection molding facility in Turkey.

Table 2
The importance weight comparison between optimum points and the optimal alternative

	Optimum alternative	$X_1^{'}$	$\cdots$	$X_m^{'}$
Optimal Alternative	Weights	$w_{X_1^{'}}$	$\cdots$	$w_{X_m^{'}}$
Θ	w_Θ	$w_{X_1^{'}}/w_\Theta$	$\cdots$	$w_{X_1^{'}}/w_\Theta$

with other methods in 17 and 7 articles, where it follows by AHP with 15 and 6 articles, ANP with 1 and 7, VIKOR with 7 and 1 articles, and DEMATEL with 6 and 1 articles respectively. It should be noted that all these methods are simply analysing decision matrices with least interference of DMs' desire and expectations, however, in many real life situations, propensity and knowledge of DMs play important roles to engender the most appropriate problem-specific decision.

2.2. MCDM method applications on food supplier evaluation/selection

As already apprehended in the previous section, evaluation and selection of the potential supplier in food sector extensively deal with MCDM methods, this section provides some examples of novel applications of MCDM methods solely, or in combined/ integrated forms for evaluation/selection of suppliers in food sector.

AHP and TOPSIS are the two majors MCDM methods which are used in supplier evaluation/selection problems in food sector. Leung, Lau, Nakandala, Kong, and Ho (2020) employed fuzzy AHP-TOPSIS framework to evaluate suppliers of a fresh food (fruits) retailer where AHP was specifically employed for criteria weight determination, while TOPSIS method was used for ranking of the considered suppliers. Kamble and Raut (2019) employed an integrated model of Delphi-AHP methods to evaluate and prioritize potato suppliers for a chip manufacturer in India. Another application of AHP can be found in (Fu, 2019) where an integrated model of AHP, additive ratio assessment (ARAS), and multi-choice goal programming (MCGP) was applied for ABC airline catering supplier selection problem. To rank potential soybean suppliers of a food processing company in Vietnam, Wang, Nguyen, Thai, Tran, and Tran (2018) proposed a hybrid model using fuzzy AHP and green DEA in order to determine criteria weights in accordance with the opinions derived from procurement experts. Lau, Nakandala, and Shum (2018) developed a business process decision model based on Fuzzy AHP, TOPSIS and ELECTRE methods for analysing food suppliers of two supermarket chains in Australia through consideration of several dependent variables like food safety, price, serviceability and commercial position. Another hybrid model weaved with ANP can be found in the study of Tavana, Yazdani, and Di Caprio (2017) in which an integrated model of ANP and quality function deployment (QFD) methods were used in order to find criteria weights and also exploited weighted aggregated sum product assessment (WASPAS) and multi-objective optimisation based on ratio analysis (MOORA) methods for supplier ranking for an Iranian dairy company. Shen and Liu (2012) proposed an integrated framework of ANP and DEMATEL methods to evaluate and identify the best food supplier through analysing cost, delivery, quality, service, technology and branding factors.

2.3. Selection of criteria related to hypermarket supplier selection problems

Suppliers play a pivotal role in food industry and hence, supplier selection process requires a logical guideline and adequate dimensions for supplier evaluation criteria to determine the most suitable

Table 3
WLD method comparison process where $C_i = C_j$.

$w_j^{'}$		C_1	$\cdots$	C_k	$\cdots$	C_n	W_i	L_i	D_i	S_i	w_i
$w_1^{'}$	C_1	D		WLD_{1k}		WLD_{1n}					
$\vdots$	$\vdots$		$\vdots$		$\vdots$	$\vdots$					
$w_k^{'}$	C_k	WLD_{k1}		D		WLD_{nk}					
$\vdots$	$\vdots$		$\vdots$		$\vdots$	$\vdots$					
$w_n^{'}$	C_m	WLD_{m1}		WLD_{mk}		D					

alternative supplier (Ramlan, Bakar, Mahmud, & Ng, 2016). Supplier selection is a complex MCDM problem which deals with the various criteria particularly in case of food sector. In this section, we reviewed those papers which recommended different food supplier evaluation criteria for hypermarkets.

La Scalia, Settanni, Micale, and Enea (2016) pointed out that decomposition of food items like chees depends on several physical factors like temperature, oxygen, humidity, light, cosmological contamination, moistness, acidity, microbiological growth and enzyme activities. These make evaluation of cheese suppliers challenging and vital for the sellers like hypermarkets. Lau, Shum, Nakandala, Fan, and Lee (2020) studied a case of small-sized supermarket chain operator of Hong Kong for analysing organic food product suppliers with eleven main criteria and multiple sub-criteria including 1. **Availability**, reliability, value-added activities (cutting, trimming, grading, and packing), packaging, warranty, and innovation; 2. **Quality** comprising conformance to specification, rejection and return rate, process capability, quality management systems, quality improvement, and quality assessment technique; 3. **Product management**, procedural compliance and periodic audits at pre- and post-farm stages, continuous food safety training, and traceability; 4. **Cost of monitoring** including probability of organic food supplier producing non-organic food, and frequency of sampling organic products for laboratory testing; 5. **Price** consisting of price representation, price decreased ratio, product cost, total logistics management cost, tariff and taxes, quantity discounts, payment terms, and shelving and listing fees; 6. **Delivery** focusing on delivery on time, lead time, compliance with quantity and packaging standards, use of standard cradles, transportation facility, e.g. refrigerated trucks, delivery performance, ability and willingness to expedite order, and delivery frequency; 7. **Serviceability** consisting of service quality, flexibility in product mix, volume, and lead time, responsiveness to demand changes, ability to modify product/service, information sharing, edi capability, and systems compatibility, technical support, management of complaints, administration for return, sell-back, and reverse logistics, and value-added service; 8. **Commercial position** allocated to the market reputation, market share, performance history, asset specificity and infrastructure, financial position and stability, and technological capability; 9. **Supplier relationship** including relationship connectors, duration of relationship. Annual average amount of past business over the last three years, communication and conflict resolution, and long-term commitment; 10. **Risk factors** including geographical location, political stability and government policies, exchange rates and economic position, labor relations, terrorism and crime rate; 11. **Corporate social responsibility** (**CSR**) including ISO-14001 certification, eco-labeling, stakeholder relations and community recognition, pay rates, labor conditions and work environment, and compliance to international human rights.

Banaeian, Mobli, Nielsen, and Omid (2015) extracted four main aspects of criteria from the past studies including 1. Financial, which embraced capital and financial power of supplier company, proposed raw material price, and transportation cost to the geographical location (Availability); 2. Delivery & service which included communication System (willing to trade, attitudes, acceptance of procedures and flexibility), on time delivery (lead time), after sales service (policy, quality assurance, and damage ratings), and production capacity; 3. Qualitative consisting of quality (the supplier ability to access the quality characteristics), operational control (reporting, quality control, inventory control, research and development), expert labor, technical capabilities and facilities, business experience and Position among competitors; 4. Environmental management system comprising of environmental prerequisite (environmental staff training), environmental planning (program to reduce environmental impacts, green research and development), environmental friendly material (low waste: easily recycling and reuse capability), and environmental friendly technology (emission of pollutant). In line with former study, Yuan, Zhang, Di, Wu, and Yang (2015) categorized the criteria in four groups of strengths, weaknesses, opportunities, and threats for assessing fresh food suppliers of a large supermarket. Following those categories, they delineated eight major criteria to evaluate fresh food suppliers consisting of price, delivery time, quality, R&D capability, service, competence, business strategy, and organizational management.

3. Ranking based on optimal points

Zakeri (2019) propounded the concept of RBOP on the notion of human behaviour pattern and cognitive science for solving MCDM problems. In contrast to other MCDM methods, RBOP does not extract the best alternative from decision matrix itself; rather it is based on finding the best alternative according to the desires of DMs by imitating human behaviour. To formulate the philosophy, RBOP first defines two groups of alternatives which are originated from outside of the problem. These alternatives are called optimum points and optimal points. In accordance with RBOP policy, the alternative which is located at the shortest distance from the optimum and optimal points simultaneously is considered as the best. As an algorithm that emulates human behaviour in analysing the process of decision matrices, RBOP naturally faces uncertainties due to human judgement and most importantly for the use of linguistic variables, as frequently used by DMs.

3.1. Optimum alternative

According to RBOP ideology, when a DM investigates alternatives individually, s/he makes an abstract alternative for each alternative where number of new alternatives is equal or more than the problem's alternatives. DMs may compare each alternative with two or more abstract alternatives. These alternatives are called optimum alternatives which do not have an independent existence. In fact, DMs match existent alternative with the manipulated alternatives to evaluate it in the decision-making process against some specific pre-defined criteria. To craft an abstract image of the optimum alternative, DMs may compare the alternative with other alternatives which are irrelevant to decision matrix and also likely have an independent existence. There are three conditions need to be met by each optimum alternative. Let us assume S_i is the overall score of the i^{th} alternative and $S^{'}_m$ is the overall score of its corresponding optimum alternative, then conditions are $(S^{'}_i < 2S_i)$, $((S^{'}_i/S_i). > 1)$, and $(D_i < S_i)$ where D_i epitomizes distance between overall scores of the optimum alternative and i^{th} alternative and $i = \{1, 2, \cdots, m\}$. Key-point of the process is the range of differences between optimum alternatives and actual alternatives. Understanding of these differences leads the DMs to a specific interpretation which indeed forms the first evaluation step of RBOP.

3.2. Optimal alternative

According to RBOP's philosophy, any alternative cannot reach the decision-making goal(s) or be optimized in every criterion it is investigated upon. Hence, RBOP's second pivotal concept is the optimal point. Based on the definition proposed by Zakeri (2019), optimal alternative is the best alternative, which meets needs of all decision-making objects. The optimal alternative is an abstract alternative, which is fabricated around its actual corresponding alternative; however, the optimal alternative, by contrast, in most cases, has independent existence, which could be potentially unearthed outside of the decision matrix as a tangible physical entity. In every decision-making problem, there is merely one optimal point. In contrary to optimum alternatives, optimal alternative has the idiographic entity but it is not accessible to the DMs. As the most desirable alternative, DMs utilize optimal alternative to make their decision output closer to it.

Analogous to optimum alternatives, each optimal alternative follows some basic rules where 1. In each criterion, optimal alternative always possesses a larger value than the problem's alternatives; 2. In each criterion, value of an optimal alternative is greater than or equal to the optimum alternative. Otherwise speaking, each optimum alternative could be possibly an optimal alternative where in this case, its corresponding alternative is the best.

4. Methodology

This section is divided into two parts. The first part includes proposition of the new RBOP algorithm, which consists of eleven simple steps to operate with crisp decision values. In the second part, WLD method is described to serve as the weighting method for RBOP based on complete information from the DMs.

4.1. RBOP with crisp values

RBOP was originally developed for grey environment. As evaluation of cheese suppliers is influenced by a mix of linguistic and non-linguistic variables, RBOP algorithm has been developed with crisp values as follows:

Step 1. Constructing decision matrix and the optimum decision matrix, where X and $X^{'}$ are the decision matrix and the optimum decision matrix.

$$X = \left[x_{ij}\right], \quad i = \{1, 2, \cdots, m\}, \quad j = \{1, 2, \cdots, n\}; \tag{1}$$

$$X^{'} = \left[x^{'}_{ij}\right], \quad i = \{1, 2, \cdots, m\}, \quad j = \{1, 2, \cdots, n\}; \tag{2}$$

Step 2. Normalization of decision matrices by following equations:

There are different normalization processes under the context of multi-conflicting criteria. In every decision matrix, criteria have dissented in benefit and cost categories. In analysis process of decision matrix, maximum value is favourable for a benefit criterion; whereas, minimum value is more conducive for a cost criterion. Normalization process for each category is indicated by Eqs. (3)–(6), where N_{ij}^{+} and N_{ij}^{-} indicate the normalized form of the benefit and cost criteria, $N_{ij}^{'+}$ and $N_{ij}^{'-}$ denote the normalized optimum benefit criteria and the optimum cost criteria respectively, and $x^{'}_{ij} \geq x_{ij}$.

$$N_{ij}^{+} = x_{ij}\left(x_{ij}^{'max}\right)^{-1} \tag{3}$$

$$N_{ij}^{-} = x_{ij}^{'min}\left(x_{ij}\right)^{-1} \tag{4}$$

$$N_{ij}^{'+} = x^{'}_{ij}\left(x_{ij}^{'max}\right)^{-1} \tag{5}$$

$$N_{ij}^{'-} = x_{ij}^{'min}\left(x^{'}_{ij}\right)^{-1} \tag{6}$$

where for the benefit and cost criteria of the decision matrix

$$x_j^{max} = \max_{1 \leq i \leq m}\{x_{ij}\} \tag{7}$$

$$x_j^{max} = \min_{1 \leq i \leq m}\{x_{ij}\} \tag{8}$$

Whilst for the benefit and cost criteria of the optimum decision matrix

$$x_{ij}^{'max} = \max_{1 \leq i \leq m}\left\{x^{'}_{ij}\right\} \tag{9}$$

$$x_{ij}^{'max} = \min_{1 \leq i \leq m}\left\{x^{'}_{ij}\right\} \tag{10}$$

Step 3. Construction of weighted decision matrix in accordance with Eqs. (11) and (12), where criteria weights are elicited from WLD method, as proposed by Zakeri (2019), w_j is the weight of criteria, and R and $R^{'}$ are the weighted decision matrix and weighted optimum decision matrix respectively. In the equations, N_{ij} denotes normalized decision matrix, and $N^{'}_{ij}$ signifies normalized optimum decision matrix.

$$R = w_j N \tag{11}$$

$$R^{'} = w_j N^{'} \tag{12}$$

where

$$N = \left[N_{ij}\right] \tag{13}$$

$$N^{'} = \left[N^{'}_{ij}\right] \tag{14}$$

$$R = r_{ij} \tag{15}$$

$$R^{'} = r^{'}_{ij} \tag{16}$$

Step 4. Computation of optimum points:

Optimum points are located on the geometric distances between an alternative and its corresponding optimum alternative. The overall score of an optimum alternative is greater than the original alternative. Hence, the optimum point inclines closer to the optimum alternative. Figs. 1 and 2 demonstrate inclination tendency of optimum points to optimum alternatives. An optimum point is inclined to the optimum alternative; nevertheless, in some criteria, the alternative is possibly has been optimized (Fig. 1), then $r_{ij} = r^{'}_{ij}$; but, in general, $r^{'}_{ij} > r_{ij}$ which force optimum point to be located closer to the optimum alternative. Alteration in location of optimum point is portrayed in Fig. 3.

The computation of optimum point is indicated by Eq. (17) which is based on Pythagorean Theorem.

$$\alpha_{ij} = \left(r_{ij}^{2} + r^{'2}_{ij}\right)^{1/2} \tag{17}$$

Step 5. Construction of optimum matrix:

$$\alpha = \left[\alpha^{'}_{ij}\right], \quad i = \{1, \cdots, m\}, \quad j = \{1, \cdots, n\}; \tag{18}$$

Step 6. Defining the optimal alternative with respect to (Eq.20), where Θ denotes optimal alternative and Θ_j is the value of optimal alternative against j th criterion.

$$\Theta = \left[\Theta_j\right] \tag{19}$$

Step 7. Normalization of optimal matrix by following equations:

$$\Theta_{N_j} = \Theta_j\left(\max_{j=n}\left\{x_{ij}, \Theta_j\right\}\right)^{-1} \tag{20}$$

$$\Theta_N = \left[\Theta_{N_j}\right] \tag{21}$$

Step 8. Construction of weighted normalized optimal matrix where w_j has been extracted from the third step.

$$\Theta^{'}_N = w_j \Theta_N \tag{22}$$

Step 9. Finding optimal points for each alternative:

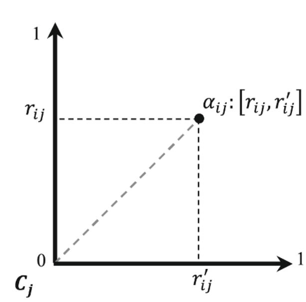

Fig. 1. Optimum point in C_j where $r_{ij} = r^{'}_{ij}$.

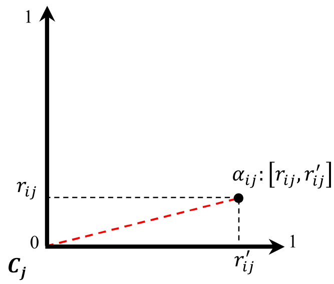

Fig 2. Optimum point in C_j where $r_{ij}^{'} > r_{ij}$.

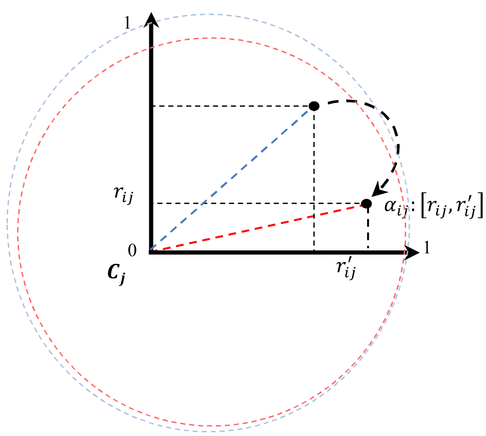

Fig. 3. Tendency of optimum points to optimum alternative.

Optimal points are positioned on the distance between optimum point and optimal alternative. Optimal point can be detected at the midpoint of distance between optimum point and optimal alternative when both possess the same value. Naturally, optimal points are oriented to more adjacent side of optimal alternative. If Φ_{ij} indicates the optimal point of i th alternative against j th criterion; then its position is shown in Fig. 4 and Fig. 5.

It can be noted that the overall score of optimal alternative is always greater than other alternatives; however, it may not be greater than optimum points. Therefore, in some criteria, optimum point is greater/equal than/to optimal alternatives. To find the position of an optimal point, difference between optimal alternative and the alternative's optimum point needs to be calculated. As argued earlier, the optimal point always tends to be closer to the optimal alternative which indeed is the result of DMs' desire in decision-making process. When DM compares the abstract alternative with the optimal alternative, s/he considers a unique importance weight for each alternative in the process. RBOP is built on the hypothesis that DMs possess complete information about the alternatives under consideration. These weights are based on how the DMs interpret importance of the alternatives. Consideration of these weights determines the position of optimal point. Hence, the first step of determination of positions of optimal points is the calculation of the mentioned weights. It is achieved through constructing a relation table between optimal alternative and each optimum alternative. In this process, DM allocates a unique weight to each alternative, including

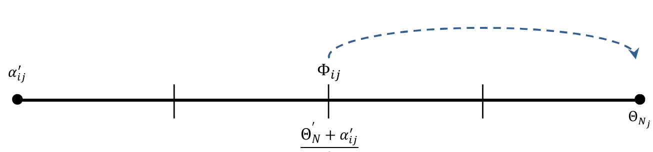

Fig. 4. Tendency of optimal point to optimal alternative, where $\Theta_{N_j} \geq \alpha_{ij}^{'}$.

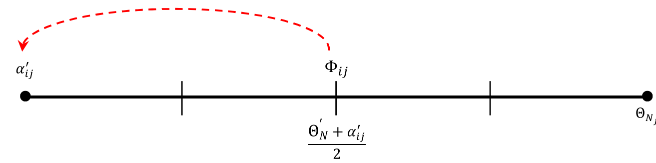

Fig. 5. Tendency of optimal point to optimal alternative, where.$\Theta_{N_j} \leq \alpha_{ij}^{'}$

optimum alternative and optimal alternatives, where importance weight of optimal alternative is greater/equal than/to optimum alternative. When the weight of each optimum alternative is equal to the weight of optimal alternative, it gets the 1st rank and considered as the best alternative.

Determination of weights of optimum alternatives has been shown in (Eqs. (23)–(26)), where $i = \{1, \cdots, m\}$ and $w_\Theta > w_{X_m^{'}}$.

$$\aleph_1 = w_{X_1^{'}} \Big/ w_\Theta \tag{23}$$

$$\aleph_i = w_{X_1^{'}} \Big/ w_\Theta \tag{24}$$

$$\aleph_i^{'} = \aleph_i \left(\sum_{i=1}^{m} \aleph_i \right)^{-1} \tag{25}$$

Thus, optimal points are calculated in accordance with Eq. (26):

$$\Phi_{ij} = \frac{\Theta_N^{'} + \alpha_{ij}^{'}}{2} \tag{26}$$

Step 10. Construction of a new decision matrix with optimal points, as extracted from former step.

$$\Phi = [\Phi_{ij}] \tag{27}$$

Step 11. Ranking of alternatives based on the descending order of $\mathscr{R}_i$ values, where greater value of $\mathscr{R}_i$ indicates better position in the ranking pre-order

$$\mathscr{R}_i = \aleph_i^{'} \sum_{i=1}^{m} \Phi_{ij} \tag{28}$$

Fig. 6 explores human behavioural pattern in any decision-making process when the DM has complete information about the criteria. The RBOP philosophy is grounded on this pattern when DM's behaviour in decision-making process when s/he possess complete information. DM's behaviour is segregated into four major sections including criteria section, section of optimal and optimum alternatives, final evaluation section, and selection section. When DM possesses perfect/complete information about the criteria, the decision-making process begins with determination of criteria based on his/her background memory and desire about optimum and optimal alternatives, followed by evaluation (to determine their weight by comparing them with each other), and concludes with the final selection.

4.2. WLD method

The first step of any decision-making process is determination of criteria by DMs through eliciting information based on their judgements and perceptions followed by weight allocation to each criterion through pairwise comparisons. Similarly, the DMs evaluate the alternative against each criterion in order to find the best one. Fig. 7 portrays the aforementioned process.

WLD is designed on the fact that DMs possess perfect information about the criteria. It is a simple weighting method in which criteria weights are calculated by imitating the pattern of human behaviour. WLD method consists of the following procedural steps:

Step 1. Allocating the first set of weights to pre-defined criteria, where $w_j^{'}$ states the wright of j th criteria. These weights are the desired

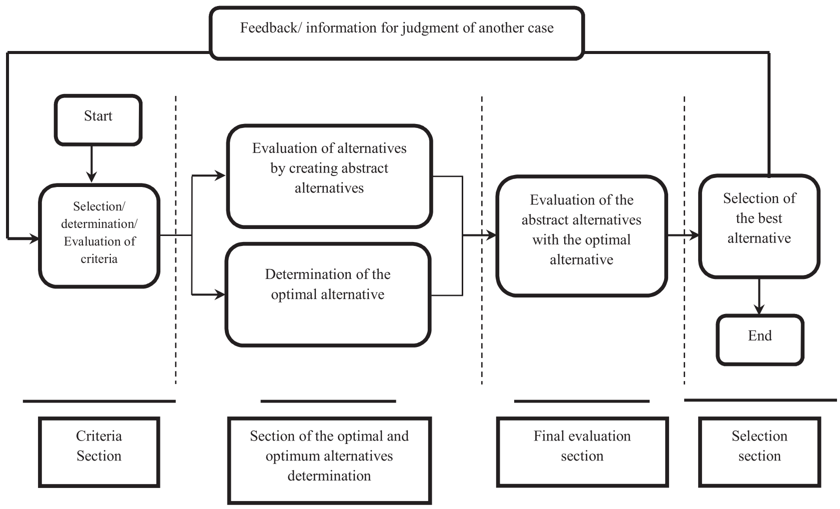

Fig. 6. The RBOP working pattern.

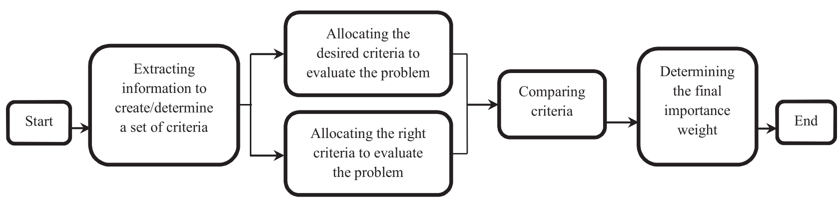

Fig. 7. Process of obtaining criteria weights.

values which DMs obtain from the very first moment of information extraction through linguistics variables.

$$w_j^{'} = \{w_1^{'}, \cdots, w_n^{'}\}, \quad j = \{1, \cdots, n\}, \quad 1 \le w_j^{'} \le 10; \tag{29}$$

To make use of linguistic variables, it is essential to transform them into numeric variables. Existing scales of AHP and ANP methods employ five categories of linguistic variables including "very low, low, moderate-low, moderate, moderate-high, high, and very high" or similar variables. Thus, $w_j^{'}$ is a rational number where:

$$w_j^{'} \in \mathbb{Q}, \mathbb{Q} : \left\{\frac{x}{y} | x \in \mathbb{Z}^+, y \in \mathbb{Z}^+, y \ne 0\right\}, \mathbb{Z}^+ \in \mathbb{N}^*, \mathbb{N}^* = \mathbb{N}\backslash\{0\} = \{1, 2, 3, \cdots\}; \tag{30}$$

$\mathbb{Q}, \mathbb{Z}^+$, and $\mathbb{N}^*$denoterationaland positive integers, and naturals without zero numbers respectively. Fig. 8 narrates the linguistic variables and their corresponding numerical values as used in WLD method. It is comprehended that WLD uses 10 as "Very Good", 5 for "Not Bad/ Not Good" and 1 for "Very Bad" to indicate corresponding importance of the criteria.

Step 2. Pairwise comparison of criteria which includes "win, loss, and draw", as the main elements of this method. DMs compare criteria unconsciously without filling any provided questionnaires with special scoring scales and policies. Hence, they use words as the main/primary tool to architect her/his cognition of the problem for evaluation the involved constituents (Auguste, Rey, & Favre, 2017; Borghi and Pecher, 2011, 2012; Borghi, Scorolli, Caligiore, Baldassarre, & Tummolini, 2013; Borghi, 2019; Glenberg & Gallese, 2012; Glenberg & Kaschak, 2002; Hollenstein, de la Torre, Langer, & Zhang, 2019). To formulate the aforementioned procedure, three values including 1, 2, and 3 have been allocated to each element, where the winner gets 3, draw gets 1, and 0 goes for the loser (Fig. 9 for two different criteria).

Three states of k th C and n th C have been shown in Fig. 9, where $j = \{1, \cdots, k, \cdots, n\}$. The following table illustrates the paradigm that utilizes for managing the operations of the comparison process.

The final product of WLD method is the W_j in which utilizes in the RBOP formula. To compute it, the above table needs to be analysed by following equations where $i = \{1, \cdots, k, \cdots m\}$ and $j = \{1, \cdots, k, \cdots n\}$.

$$W_i = \sum_{j=1}^{n} W_{mn} \tag{31}$$

$$L_i = \sum_{j=1}^{n} L_{mn} \tag{32}$$

$$D_i = \sum_{j=1}^{n} D_{mn} \tag{33}$$

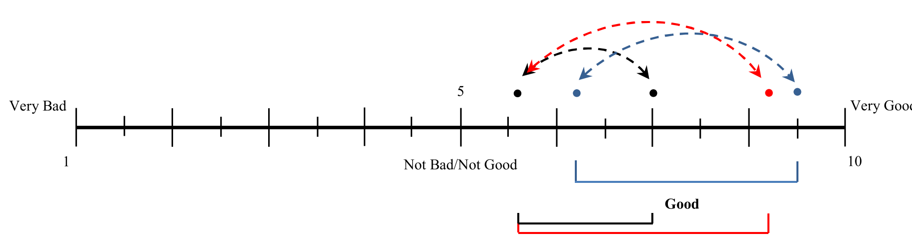

Fig. 8. Linguistic patterns as used in WLD method.

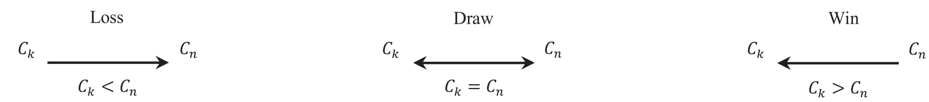

Fig. 9. Schematic comparison process of WLD method.

$$S_i = W_i + L_i + D_i \tag{34}$$

$$w_i = w_j \tag{35}$$

$$w_j = \left(\sum w'_j S_i\right)^{-1} w'_j S_i \tag{36}$$

Results of the above formulae are used as criteria weights in RBOP algorithm.

5. Application and results

This section is focused on the implementation and validation of the new form the RBOP in a hypermarket located in Tehran, Iran. This section is divided into three divisions. In the first division, the hypermarket has been introduced in a brief introduction; the data collection has been performed in the second division, and the third section is dedicated to the implementation of the RBOP to evaluate the alternatives in order to find the best supplier. There is a lack of published information regarding dairy industries in Iran (Zakeri, Delavar, & Cheikhrouhou, 2020). In this paper, all utilized data have been collected by the sales and marketing department of the head office and the branch's sales department. The data collection process incorporates interview with the hypermarkets' managers, filling questionnaires by sellers and the operations staffs, and interchanging assessment documents between the companies and the hypermarket branches. The assessments have been performed by the experts including 1. the branch's manager, who is in charge of the whole business operations of the branch; 2. sales department director and the head office's, who has access to a large range of the information regarding the companies, their product portfolio and the changes of trends related to the markets, sells, promotions, prices, and products. sales and marketing manager of the hypermarket who covered the information regarding the products, the customers' behavioural patterns; and the logistic and transportation manager who is in charge of the transportation and the logistic operations.

5.1. The hypermarket

In this paper, supplier selection case study for a hypermarket cheese store is considered which is located in Tehran. It is one of the main stores from 1500 branches of the Iranian hypermarket chains and has confined its product portfolio to almost 800 items and offers essential consuming products only. Its policy focuses to minimize its operational costs in an attempt to provide reasonable price and high-quality products to its customers. Dairy product portfolio has the highest demand due to its daily consumption rate. Four main groups of dairy products are supplied in the hypermarkets that include more than 150 product varieties. The main groups are cheese products, dairy beverage products, yoghurt products, and cream and butter products.

The current cheese products in domestic market are Parmigiano-Reggiano, Gouda cheese, Pecorino Romano, Camembert, Gorgonzola, Blue cheese, Pesto cheese, Prato Butterkäse, Shropshire Blue, Cheddar cheese, Mozzarella, Parmigiano-Reggiano, Ultra-filtered cheese (UF cheese), Cream Cheese, Feta Cheese, Lactic Cheese, Lighvan Cheese and Khikki Cheese. Most of them are supplied by Kalleh, while other companies focus to produce Feta cheese, UF cheese, Cream cheese, Lactic cheese and Lighvan cheese. This store evaluates cheese suppliers through ten criteria in order to select the best supplier among Mihan[1], Haraz[2], Damdaran[3], Alima, Pegah[4], Sabbah[5], Gela[6], and Domino[7].

5.2. Data collection

In order to evaluate the suppliers, a set of criteria has been collected consisting of 1. Appropriateness of product price; 2. Number of product promotions per year; 3. Ability to adapt to increase, decrease, and change order of timing; 4. Make-to-order production; 5. Delivery reliability; 6. Variety; 7. Brand equity; 8. Defect Rate; 9. Reliability of quality; and 10. After sales services. These criteria are abbreviated as $C_j = \{C_1, C_2, C_3, C_4, C_5, C_6, C_7, C_8, C_9, C_{10}\}$. Due to state capitalism system which shapes domestic market behaviour, Iranian government determines price of goods and controls competition. The government merely controls higher bound of prices; thus, some companies find their competitive advantages by reducing product price than market price usually in a range of 5% – 7.5%. Hence, we considered the number of promotions (C2) which signifies the times that companies discount their products' prices. Another issue that hypermarkets are facing is the varied order timings due to inventory issues and transportation problems. On the other hand, due to unpredictability in sales, real orders are more than pre-orders; especially during peak seasons. Thus, hypermarkets need to work with flexible suppliers.

In general, some evaluation processes deal with human judgments, which in most cases function with linguistic variables. Table 4 presents a scale for translating linguistic variables into numerical values.

As shown in Table 4, corresponding numbers for each linguistic variable have been assigned with a crisp number. Various studies benefit from the scales proposed with fuzzy numbers to transform the qualitative/linguistic factors to quantitative parameters in order to deal with the uncertainty which generate inherently during the transformation, for instance, Tosarkani and Amin (2018) employed fuzzy ANP to deal with the qualitative variables to select the best third party for configuring an electronic reverse logistics network. Yet, since the experts possess complete knowledge regarding the assessment of the relations between alternatives and criteria, the aforementioned scale is proposed

Table 4
Linguistic variables and their corresponding numerical values for criteria rating

Linguistic variables	Numerical value
Very Poor (VP)	1
Poor (P)	2
Medium Poor (MP)	3
Fair (F)	5
Medium Good (MG)	7
Good (G)	9
Very Good (VG)	10

[1] www.mihan-dairy.com
[2] http://harazdairy.com/
[3] http://damdaran.ir/en
[4] http://pegah.ir/
[5] www.sabahdairy.ir/
[6] www.geladairy.com/
[7] www.dominodairy.com/

to serve the process. It is one of the limitations of the RBOP with crisp numbers which has been discussed in the further sections. Thus, the supplier evaluation decision matrix has been illustrated in Table 5, where (+) and (−) stand for benefit and cost criteria respectively.

With respect to Table 4, Fig. 10 shows the designated scale to evaluate variety of products, where each number represents the number of cheese products offered by each company to its customers.

5.3. Application and results

According to the DM's decision-making behavioural pattern (see Fig. 6), the first step is the analysis of problem criteria. In order to simulate the decision-making process, RBOP benefits from WLD method to analyse criteria weights using Eqs. (31) –(36). To run WLD method, DMs need to share their judgments before initiation of pairwise comparisons. According to Eqs. (29) and (30), the following set represents preliminary weights of criteria.

$$w_j^{'} = \{7, 9, 8, 7, 9, 5, 9, 7, 7, 5\}$$

Second step of WLD process is associated with pairwise criteria comparisons, as shown in Table 6.

The weights extracted from (Table 6) are as the following set:

$$S_i = \{119, 198, 128, 105, 144, 20, 198, 91, 56, 5\};$$

$$w_j = \{0.112, 0.186, 0.12, 0.099, 0.135, 0.019, 0.186, 0.086, 0.053, 0.005\};$$

The next step is defining optimum alternative for each supplier. This process begins with analysing each supplier by the DMs and consequently, abstract alternatives are created using DMs' preferences. These new crafted-suppliers are called optimum suppliers, as demonstrated in Table 7.

To determine locations of optimum points, two decision matrices need to be normalized using Eqs. (3)–(5) respectively. Fig. 11 exhibits differences between each supplier and its corresponding optimum supplier. Since, the optimum points are positioned on geometric distance between alternatives and optimum alternatives, these figures indicate conformities and nonconformities of the suppliers and their optimum suppliers.

In Fig. 11, Pegah shows more conformity with its optimum which makes it as a potential alternative to be the best supplier. On the other hand, Domino shows less conformity with its optimum which makes it the worst chees supplier consequently. The next step prior to the determination of optimum points is the calculation of weighted normalized matrices, as given in Tables 8 and 9 respectively (Table 10).

Optimum points are laid on the distances between the alternatives and their optimums. Tendency of the optimum points is to become closer to optimum alternatives. Eq. (17) is used to locate the optimum points as shown below.

$$\alpha = \begin{bmatrix} 0.1068 & 0.2122 & 0.1188 & 0.1089 & 0.1725 & 0.0155 & 0.2630 & 0.0580 & 0.0523 & 0.0057 \\ 0.1584 & 0.1908 & 0.1527 & 0.1400 & 0.1725 & 0.0269 & 0.2630 & 0.0141 & 0.0382 & 0.0042 \\ 0.1068 & 0.1908 & 0.1527 & 0.1089 & 0.1546 & 0.0155 & 0.2051 & 0.0328 & 0.0606 & 0.0057 \\ 0.1230 & 0.1808 & 0.1235 & 0.1089 & 0.1546 & 0.0155 & 0.2051 & 0.0233 & 0.0606 & 0.0057 \\ 0.1230 & 0.2630 & 0.1188 & 0.1089 & 0.1725 & 0.0162 & 0.2051 & 0.0304 & 0.0523 & 0.0057 \\ 0.1068 & 0.1577 & 0.1697 & 0.1400 & 0.1344 & 0.0162 & 0.1457 & 0.0198 & 0.0523 & 0.0058 \\ 0.1584 & 0.1754 & 0.1527 & 0.1133 & 0.1651 & 0.0191 & 0.1109 & 0.0879 & 0.0750 & 0.0058 \\ 0.1418 & 0.1779 & 0.1235 & 0.0946 & 0.1725 & 0.0191 & 0.2051 & 0.0524 & 0.0551 & 0.0057 \end{bmatrix}$$

In addition, optimal points are the other pivotal concepts of RBOP method. In order to locate these points, optimal alternative needs to be defined. The optimal alternative has an independent existence and is not accessible to the DMs. In this problem, optimal alternative is the Kalleh brand. Signifying that the DMs aim to prioritize the suppliers according to their optimums and the Kalleh brand. To rank the suppliers, Kalleh plays role of optimal alternative and does not have a direct effect on the decision matrix. In contrast to optimum alternative, data structure of optimal alternative is architected based on the real information. Hence, as the optimal supplier, Kalleh brand analysis against the criteria has been exposed in the following set, where Θ symbolizes Kalleh.

$$\Theta = \{VG, 18, G, VG, VG, G, VG, 0.01, VG, G\}$$

As discussed before, in some criteria the optimum point is greater/equal than/to the optimal alternatives. The normalized and weighted normalized optimal alternative are as following.

$$\Theta_N = \{1, 1, 0.9, 1, 1, 1, 1, 0.111, 1\}$$

$$\Theta_N^{'} = \{0.112, 0.186, 0.108, 0.099, 0.135, 0.019, 0.186, 0.889, 0.053, 0.005\}$$

To find the optimal points, first, the importance of the optimal alternative and optimum alternative needs to be calculated. The

Table 5
Cheese supplier evaluation decision matrix.

	+	+	+	+	+	+	+	−	+	+
	Appropriateness of the product price to the market price	Numbers of Promotion times	Ability to adapt to increase, decrease, and change of order timing	Make-to-order production	Delivery reliability	Variety	Brand equity	Defect Rate	Reliability of quality	After sales services
Mihan	F	14	MG	MG	G	P	G	0.021	MG	MG
Pegah	G	12	G	G	G	G	G	0.090	F	F
Haraz	F	12	G	MG	MG	P	MG	0.043	MG	MG
Damdaran	MG	9	F	MG	MG	P	MG	0.054	MG	MG
Sabbah	MG	18	MG	MG	G	MP	MG	0.041	MG	MG
Alima	F	6	VG	G	MG	MP	F	0.063	MG	F
Gela	G	12	G	F	MG	VP	P	0.047	VG	F
Domino	MG	10	F	F	G	VP	MG	0.029	F	MG

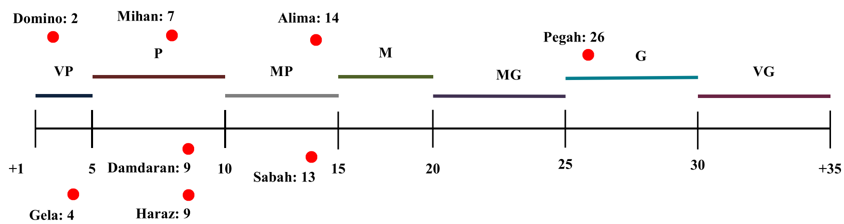

Fig. 10. Evaluation scale for the variety of the products criterion.

Table 6
The comparison matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
C_1	*D*	*D*	*W*	*L*	*D*	*W*	*D*	*D*	*W*	*W*
C_2	*D*	*D*	*D*	*W*	*W*	*W*	*D*	*W*	*W*	*W*
C_3	*L*	*D*	*D*	*W*	*W*	*W*	*L*	*D*	*D*	*W*
C_4	*W*	*L*	*L*	*D*	*D*	*W*	*L*	*D*	*W*	*W*
C_5	*D*	*L*	*L*	*D*	*D*	*W*	*D*	*W*	*W*	*W*
C_6	*L*	*L*	*L*	*L*	*L*	*D*	*L*	*L*	*L*	*W*
C_7	*D*	*D*	*W*	*W*	*D*	*W*	*D*	*W*	*W*	*W*
C_8	*D*	*L*	*D*	*D*	*L*	*W*	*L*	*D*	*W*	*W*
C_9	*L*	*L*	*D*	*L*	*L*	*W*	*L*	*L*	*D*	*W*
C_{10}	*L*	*L*	*L*	*L*	*L*	*L*	*L*	*L*	*L*	*D*

calculation process performs by constructing a comparative relation matrix which has been exhibited in (Table 11). RBOP designed for the situations where DMs possess perfect information about the decision-making's problem. In this case, due to the periodic supplying of different brands, the hypermarket possess complete information of cheese suppliers.

Finally, the ranking of alternatives is in Table 11.

The last step of the RBOP algorithm is ranking of alternatives where:

$$Pegah > Mihan > Damdaran > Haraz > Alima > Sabbah > Gela > Domino$$

Hence, as exhibited in (Table 11), Pegah conquered first rank, while, Domino stood on the last stage, where Φ_{ij} , $\aleph_i^{'}$, and $\mathscr{R}_i$ are obtained from (Eq. (26)), (Eq. (25)), and (Eq. (28)). As described in Fig. 1, amongst the problem's alternative, the one that has the least difference with its corresponding optimum alternative possibly is the best alternative, while, potentially, the highest difference leads the alternative to be the worst alternative.

6. Comparison

This two-part section focuses on the comparison of the EBOP algorithm with other existing MCDM methods. In the first part, the results of the cheese suppliers' evaluation by different MCDM methods have been compared with the results derived from RBOP algorithm performance. In the latter part, outputs of the RBOP algorithm with the application of the different weights obtained from several MCDM weight methods have been compared.

6.1. RBOP and other MCDM methods

In MCDM application cases, usually, when the results of a novel method or approach compare with other methods' results, the purpose is the validation of that method or approaches. In general, these comparisons envelop the complexity of approaches and less computation, time of calculation, the applicability of the integration with other MCDM methods, dealing with linguistic and non-linguistic variables, etc., to shows better/equal performances of the novel method or approach. However, the different results are highly expected when DM(s) use RBOP to find the solution for the decision-making problem. Thus, in this section, the purpose of the comparison is to represent and discuss the quiddity of the difference between outputs of the RBOP algorithm with other MCDM techniques' outputs. To achieve the mentioned purpose, the RBOP results have been compared with TOPSIS, SAW, VIKOR, COPRAS and MOORA methods' results. VIKOR is grounded into compromise programming, as it is designed to devise a solution that is the closest to an ideal one (Ouenniche, Bouslah, Perez-Gladish, & Xu, 2019). Developed by Brauers and Zavadskas (2006), consisting of two parts, namely the ratio system and the reference point approach (Brauers, 2013; Hafezalkotob, Hafezalkotob, & Sayadi, 2016), Multi-objective optimisation on the basis of ratio analysis (MOORA) method has been introduced in order to solve various complex and conflicting decision-making problems (Bera, Jana, Banerjee, & Nandy, 2019). As mentioned, this section intends to show the difference between the RBOP and other MCDM methods. Stemmed from the fact that the RBOP algorithm impersonates human behaviour, one of the main differences between RBOP and the other MCDM methods is that DM possesses enough information, which makes her/him be able to imagine what alternative s/he wants as the best alternative, the alternatives analysis's output by MCDM methods. On the contrary, other MCDM algorithms "decide" which alternative could be potentially the best alternative, while, DM has no perspective of the final results. The reason we used the verb of deciding here is difference between outputs of MCDM methods due to employing different algorithms and philosophies. The results of aforementioned MCDM methods application have been shown in (Table 12).

The comparative analysis between the rankings executed by the RBOP, TOPSIS, SAW, VIKOR, COPRAS, and MOORA has been exhibited in (Fig. 12).

Table 7
Optimum suppliers

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Mihan	MG	15	MG	MG	G	MG	G	0.021	MG	MG
Pegah	G	14	G	G	G	G	G	0.090	F	F
Haraz	MG	14	G	MG	G	MG	MG	0.033	G	MG
Damdaran	MG	15	G	MG	G	MG	MG	0.050	G	MG
Sabbah	MG	18	MG	MG	G	MG	MG	0.040	MG	MG
Alima	MG	14	VG	G	MG	MP	F	0.060	MG	G
Gela	G	12	G	G	VG	G	F	0.010	VG	G
Domino	G	14	G	MG	G	G	MG	0.020	G	MG

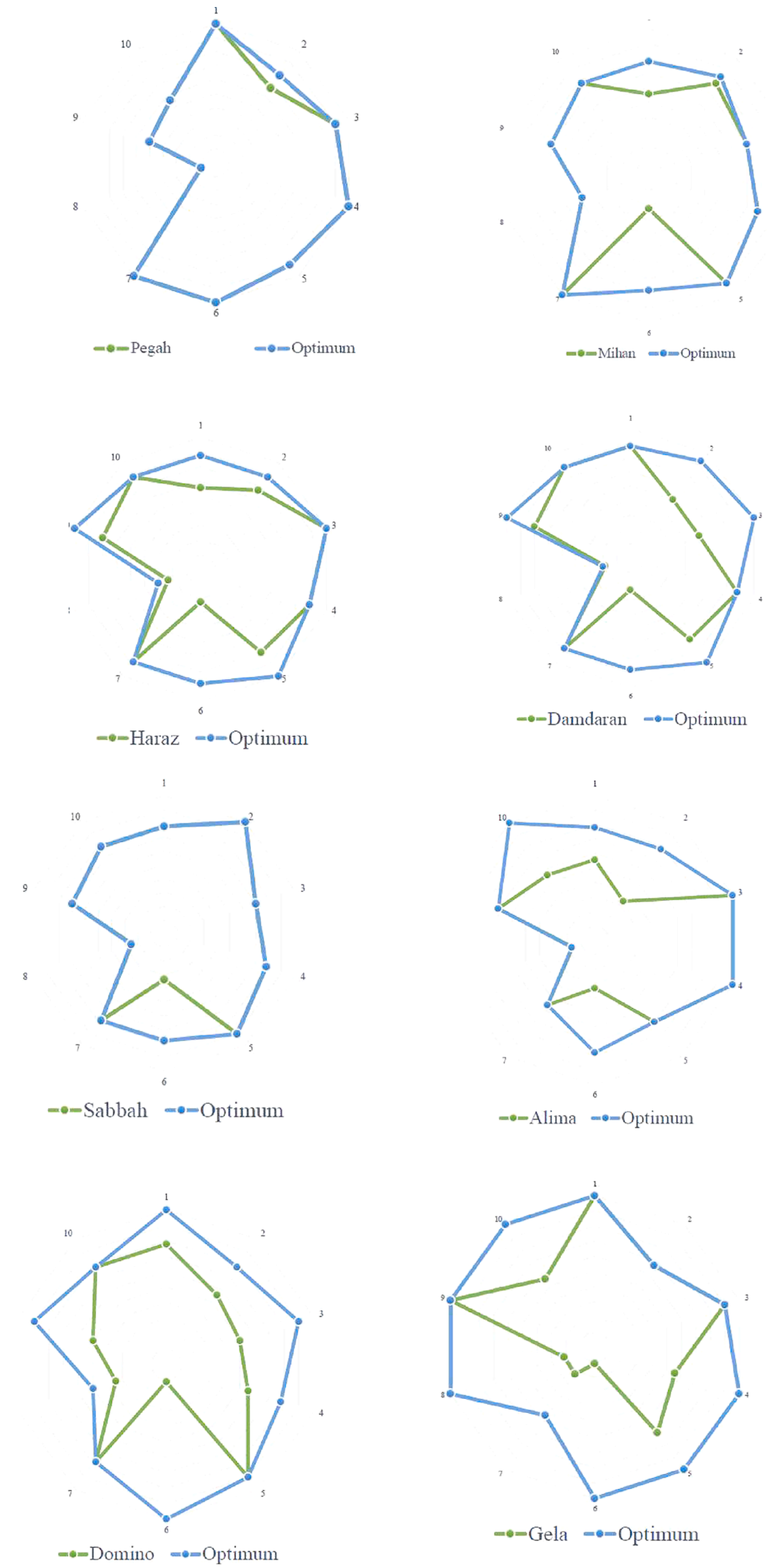

Fig. 11. The comparison between cheese suppliers and their corresponding optimum suppliers.

Table 8
Weighted decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Mihan	0.062	0.145	0.084	0.077	0.122	0.004	0.186	0.041	0.037	0.004
Pegah	0.112	0.124	0.108	0.099	0.122	0.019	0.186	0.010	0.027	0.003
Haraz	0.062	0.124	0.108	0.077	0.095	0.004	0.145	0.020	0.037	0.004
Damdaran	0.087	0.093	0.060	0.077	0.095	0.004	0.145	0.016	0.037	0.004
Sabbah	0.087	0.186	0.084	0.077	0.122	0.006	0.145	0.021	0.037	0.004
Alima	0.062	0.062	0.120	0.099	0.095	0.006	0.103	0.014	0.037	0.003
Gela	0.112	0.124	0.108	0.055	0.095	0.002	0.041	0.018	0.053	0.003
Domino	0.087	0.103	0.060	0.055	0.122	0.002	0.145	0.030	0.027	0.004

Table 9
Weighted optimum decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Mihan	0.087	0.155	0.084	0.077	0.122	0.015	0.186	0.041	0.037	0.004
Pegah	0.112	0.145	0.108	0.099	0.122	0.019	0.186	0.010	0.027	0.003
Haraz	0.087	0.145	0.108	0.077	0.122	0.015	0.145	0.026	0.048	0.004
Damdaran	0.087	0.155	0.108	0.077	0.122	0.015	0.145	0.017	0.048	0.004
Sabbah	0.087	0.186	0.084	0.077	0.122	0.015	0.145	0.022	0.037	0.004
Alima	0.087	0.145	0.120	0.099	0.095	0.015	0.103	0.014	0.037	0.005
Gela	0.112	0.124	0.108	0.099	0.135	0.019	0.103	0.086	0.053	0.005
Domino	0.112	0.145	0.108	0.077	0.122	0.019	0.145	0.043	0.048	0.004

As displayed in the above figure, there is a salient difference between outputs of RBOP with other MCDM results. Subsequently, there could be considerable dissimilarity distinguished in Sabbah and Damdaran rankings. Moreover, Mihan and Pegah have been selected almost by all methods as the best suppliers in which it shows that even though these suppliers are more desirable for the hypermarket, other MCDM methods also selected them as the best suppliers. Indeed, the anomalies of ranking, Damdaran and Sabbah, are generated by effects of the optimum and optimal points. Furthermore, taking into account the fact that RBOP rankings process directly relies on the weights produced by the WLD method, and to compare MCDM results, the products of the WLD method have been applied in the computation in all MCDM techniques, it potentially can imply the similarity between the first ranks. For examining the aforementioned hypothesis, the outputs of MCDM methods have been compared by applying preliminary weights of criteria by DM adopted from WLD method (Figs. 14 and 15).

$$w_j^{'} = \{7, 9, 8, 7, 9, 5, 9, 7, 7, 5\}$$

Since ($\sum w_j^{'} = 1$), to derive the MCDM methods' outputs, the following normalized weights have been employed. For normalizing the weights, we applied simple average. The normalized weights are as following:

$$w_j^{'} = \{0.096, 0.123, 0.110, 0.096, 0.123, 0.068, 0.123, 0.096, 0.096, 0.068\}$$

By the impact of the new weights, the new rankings can be found in Table 13.

As could be explicitly observed, utilizing the preliminary weights generated the dissimilarities between rankings as we expected; however, as pictured in the figure, there are still high differences between the ranks of Mihan, Damdaran, and Sabbah similar to the previous analysis. The second section of the comparison is dedicated to the discussion of the weights produced by WLD and their effects on the rankings. In addition to the fact that the significant differences could be seen in the charts, the following simple approach has been designated to show the similarities. The approach has been established based on the distance between alternatives' rankings generated by MCDM methods implemented in one case (Table 14).

In order to initiate the computation of the similarity, a comparison table needs to be constituted as the following order, where $i = \{1, 2, \cdots, m\}, j = \{1, 2, \cdots, n\}$, q_i denotes i th MCDM method, A_j shows j $^{\text{th}}$ alternative, and x_{ij} stands for the rank of j $^{\text{th}}$ alternative produced by i $^{\text{th}}$ alternative.

The computation of the similarity degree is in accordance with (Eq. 37, 38), where $\mathfrak{s}_z$ demonstrates the similarity degree of z th MCDM method.

$$\mathfrak{s}_z^{'} = \sum_{i=1}^{m} \sum_{j=}^{n} \left(\Delta_{x_{zj}, x_{ij}}{}^{2}\right)^{1/2}, \quad z \in i, 1 \leq z \leq m; \tag{39}$$

$$\mathfrak{s}_z = \min_{1 \leq i \leq m} \mathfrak{s}_z^{'} \Big/ \mathfrak{s}_z^{'}, \quad 0 < \mathfrak{s}_z \leq 1; \tag{40}$$

The larger value of $\mathfrak{s}_z$ represents higher degree of similarity, where the method with ($\mathfrak{s}_z = 1$) possesses the highest similarity degree between the methods; likewise, we envisage the smallest value of $\mathfrak{s}_z$ and the least similarity for RBOP.

To calculate the similarity degree, there are two scenarios including the rankings with the impact of weights obtained from WLD method and the ranking with impact of preliminary weights decided by DM. In both scenarios less degree of similarity is expected. In the first scenario, the less degree of similarity shows impact of optimum points and optimal points, while, the less degree of similarity shows the impact of weights obtained from WLD method. The similarity degree of each scenario is paraded in (Tables 15 and 16).

Table 10
The comparative importance weights of optimal alternative and optimum alternatives

	Optimum							
Weight	8	8	7	8	6	7	5	5
10	Mihan	Pegah	Haraz	Damdaran	Sabbah	Alima	Gela	Domino
Kalleh	0.8	0.8	0.7	0.8	0.6	0.7	0.5	0.5
$\aleph_i^{'}$	0.148	0.148	0.130	0.148	0.111	0.130	0.093	0.093

Table 11
The ranking of alternatives

	Φ_{ij}										$\aleph_i^{'}$	$\mathscr{R}_i$	*Rank*
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}			
Mihan	0.393	0.497	0.404	0.439	0.568	0.298	0.593	0.482	0.375	0.494	0.148	0.672	2
Pegah	0.556	0.456	0.504	0.550	0.568	0.510	0.593	0.505	0.281	0.365	0.148	0.723	1
Haraz	0.393	0.456	0.504	0.439	0.516	0.298	0.483	0.495	0.431	0.494	0.13	0.586	4
Damdaran	0.445	0.437	0.418	0.439	0.516	0.298	0.483	0.500	0.431	0.494	0.148	0.660	3
Sabbah	0.445	0.593	0.404	0.439	0.568	0.311	0.483	0.496	0.375	0.494	0.111	0.511	6
Alima	0.393	0.393	0.554	0.550	0.457	0.311	0.370	0.502	0.375	0.503	0.13	0.573	5
Gela	0.556	0.427	0.504	0.454	0.546	0.365	0.304	0.467	0.527	0.503	0.093	0.433	7
Domino	0.504	0.431	0.418	0.388	0.568	0.365	0.483	0.485	0.394	0.494	0.093	0.421	8

Table 12
The ranking of the cheese suppliers by different MCDM methods

Supplier	RBOP	TOPSIS	SAW	VIKOR	COPRAS	MOORA
Mihan	2	1	3	1	3	2
Pegah	1	2	1	3	1	3
Haraz	4	4	4	2	4	4
Damdaran	3	5	6	5	5	7
Sabbah	6	3	2	4	2	1
Alima	5	7	5	6	8	8
Gela	7	8	7	8	7	6
Domino	8	6	8	7	6	5

According to Tables 15 and 16, RBOP shows the least similarity to other MCDM methods. This is directly caused by the optimum and optimal points, and the weights obtained from the WLD method which indeed proves the main two hypotheses we primly had. Possibly, the main reason of the RBOP's least similarity degree is the impact of the optimum and optimal points due to the short distances between two similarity degrees of RBOPs (See Tables 15 and 16). Yet, the outputs of the WLD method have amplified the dissimilarity as well. As the other results of the similarity degree's computation, TOPSIS and COPRAS show more resemblance to each other, and both have the highest similarity degree, while, MOORA's results in the two comparisons are closer to the RBOP's results. To test the fact that how the WLD method affects the ranking produced by RBOP, the following section has been provided.

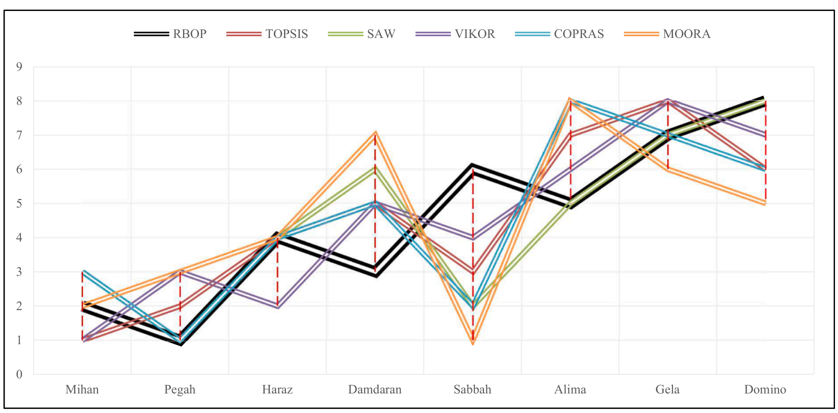

Fig. 12. The comparative analysis of different rankings operated by the MCDM methods.

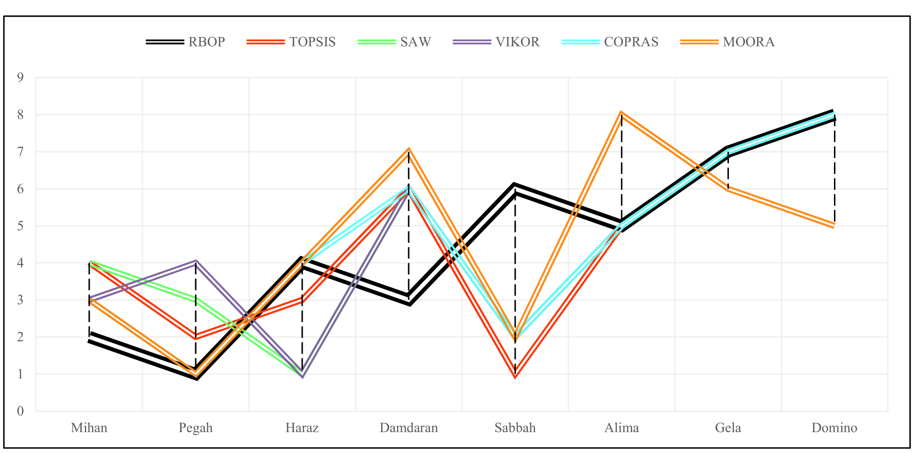

Fig. 13. The rankings comparative analysis by means of preliminary weights.

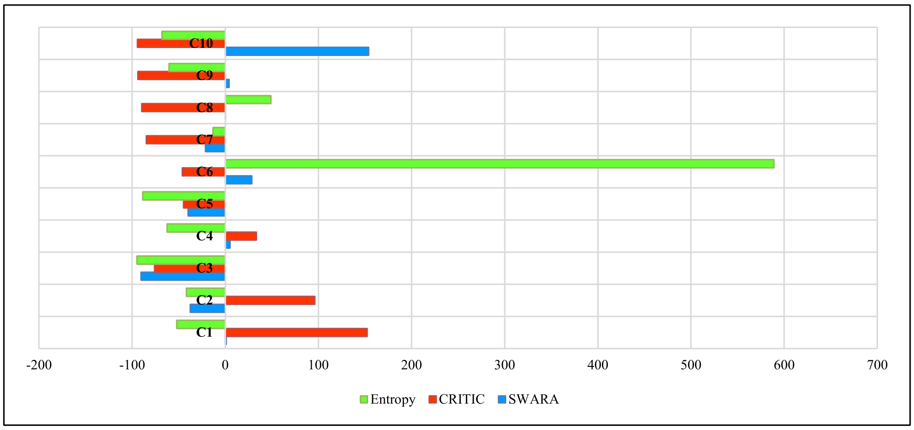

Fig. 14. Analytical comparison between preliminary weights and weights obtained from three weighting methods.

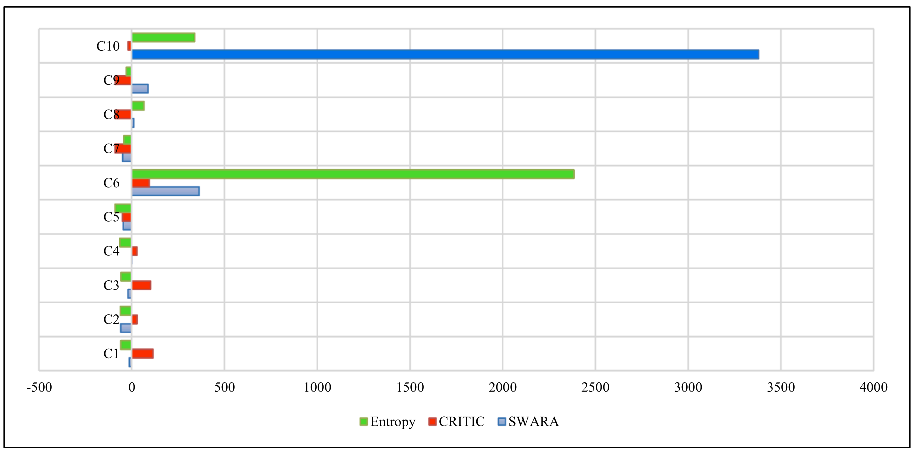

Fig. 15. Analytical comparison between outputs of WLD method and weights obtained from three weighting methods.

Table 13
The ranking of the cheese suppliers by different MCDM methods with utilization of preliminary weights

Supplier	TOPSIS	SAW	VIKOR	COPRAS	MOORA
Mihan	4	4	3	3	3
Pegah	2	3	4	1	1
Haraz	3	1	1	4	4
Damdaran	6	6	6	6	7
Sabbah	1	2	2	2	2
Alima	5	5	5	5	8
Gela	7	7	7	7	6
Domino	8	8	8	8	5

Table 14
The comparison table

	A_1	$\cdots$	A_n
q_1	x_{11}	$\cdots$	x_{1n}
$\vdots$	$\vdots$	$\ddots$	$\vdots$
q_m	x_{m1}	$\cdots$	x_{mn}

6.2. Impact of WLD method

As stated in the previous section, RBOP approach is imitating human's behavioural pattern in decision-making in order to extract the alternatives that are closer to the DM's desires; moreover, it also relies on the weights attained from WLD method in which it is established in accordance with human's behavioral pattern as well. In this section, we are trying to test the fact that the weights extorted from the WLD method have that impact in which it changes the final rankings utterly and make it closer to the DM's desires. To inaugurate comparative analysis, SWARA Method, CRITIC Method, and Entropy have been employed; then, the results of the applications of the aforementioned methods on the ranking will be compared with rankings resulted by the impact of weights obtained from the WLD method. In this process, the preliminary weights decided by DM and the weights obtained from the WLD method are playing as the indicators for the comparison process. The WLD method is categorized as a subjective weighting method. The subjective weight determination is based on the experts' opinions, and in order to get the subjective judgments, analyst normally presents the decision-makers a set of questions in the process (Odu, 2019). AHP, ANP, and BWM are examples of subjective methods. On the other hand, the objective weighting methods determine criteria weights through analysis of the decision matrix itself without taking into account the human

Table 15
Comparison based on the similarity degree with the effect of weights obtained from WLD

	Mihan	Pegah	Haraz	Damdaran	Sabbah	Alima	Gela	Domino	$\mathfrak{S}_z$
RBOP	2	1	4	3	6	5	7	8	0.429
TOPSIS	1	2	4	5	3	7	8	6	1
SAW	3	1	4	6	2	5	7	8	0.706
VIKOR	1	3	2	5	4	6	8	7	0.720
COPRAS	3	1	4	5	2	8	7	6	0.800
MOORA	2	3	4	7	1	8	6	5	0.486

Table 16
Comparison based on the similarity degree with the effect of the preliminary weights decided by DM

	Mihan	Pegah	Haraz	Damdaran	Sabbah	Alima	Gela	Domino	$\mathfrak{S}_z$
RBOP	2	1	4	3	6	5	7	8	0.402
TOPSIS	4	2	3	6	1	5	7	8	0.976
SAW	4	3	1	6	2	5	7	8	0.837
VIKOR	3	4	1	6	2	5	7	8	0.732
COPRAS	3	1	4	6	2	5	7	8	1
MOORA	3	1	4	7	2	8	6	5	0.488

judgments interference in which it usually caused inaccuracy. Some objectives methods benefit from DM's intervention in their algorithm to cover the weakness discussed in advance, such as Entropy. The three methods chosen for the comparison are a mix of objective and subjective weighting methods. SWARA is an objective method, while, the letter ones are subjective methods. The weights computed are exhibited in Table 17.

The preliminary weights and the weights computed by the WLD method are the two indicators that other weighting methods are analysed according to them. In the comparison process, we aim to investigate the variation range of weights according to the weights based on the DM's judgment and behaviour. Following figures displays the variation range of the weights in percentage compared with the weights obtained from WLD method and the preliminary weights.

As expected, SWARA shows more similarity to the preliminary weights and WLD method's outputs. As a simple MCDM method, the WLD mainly employs to compute the weights of criteria, whilst, it could be theoretically used to evaluate the decision-making problems' alternatives. The WLD number of comparisons is $(n^2 - n)/2$ which is similar to AHP, whilst, it is more than BWM. Having said that, the main advantage of the WLD is to be giving the authority to DM for revising his/her decisions through the decision-making process benefiting from a two-step algorithm. Primarily, DM has own assumptions of weighting importance of criteria which are the relative weights. In the second phase, s/he revises/validates his/her decisions through the comparison process by considering subjectively the problem's alternatives, and the optimum and optimal alternatives. With emulating the human behavioural pattern, the WLD process way simpler than AHP and BWM, while, the results are closer to the DM's desires. Furthermore, due to the fact that DM considers new concepts, which has been mentioned earlier, the two-phase algorithm does not disaffirm the reliability of the results. The WLD method also works very well with dependent and independent criteria. The difference between the relative preliminary weights given by DM and the weights resulted from the WLD method is shown in Fig. 16.

The difference variation range of the WLD methods outputs and weights given by DM mainly caused by the consideration of the alternatives, and optimum and optimal points. In other words, the preliminary weights are the relative weights that he has been set in his mind, but, setting goals of decision-making, encountering the problem's alternatives, their preliminary analysis (determining optimum alternatives and optimal alternative), and eventually reconsideration the relative weights lead him to the new weights in which the process has embodied in the WLD algorithm. Fig. 16 displays the mentioned processes' results. As argued in advance, we aim to test the hypothesis that besides the impact of optimum and optimal points, using WLD method also alters the rankings in comparing using other weighting method in RBOP. To investigate the mentioned hypothesis, two different comparisons have been provided that the first comparison focuses on the raking of the cheese suppliers by using the weighting methods and the latter concerns about the final scores of suppliers. The following figures shows the comparisons.

In spite of the fact that Pegah and Mihan are the two dominant dairy brands in the Iranian domestic market, according to Figs. 17 and 18, due to resemblance of the ranking results by applying aforesaid weighting methods, the impact of optimum and optimal points is more than WLD method's output on the final rankings which disaffirms our hypothesis. However, its direct impact on the final rankings of different MCDM methods could be observed in Fig. 12.

Table 17
Criteria weights computed by three weighting methods

Method	Appropriateness of the product price to the market price	Numbers of Promotion times	Ability to adapt to increase, decrease, and change of order timing	Make-to-order production	Delivery reliability	Variety	Brand equity	Defect Rate	Reliability of quality	After sales services
SWARA	0.097	0.077	0.096	0.101	0.074	0.088	0.097	0.096	0.100	0.174
CRITIC	0.242	0.242	0.242	0.128	0.068	0.037	0.019	0.010	0.006	0.004
Entropy	0.046	0.072	0.051	0.036	0.014	0.472	0.107	0.143	0.038	0.022

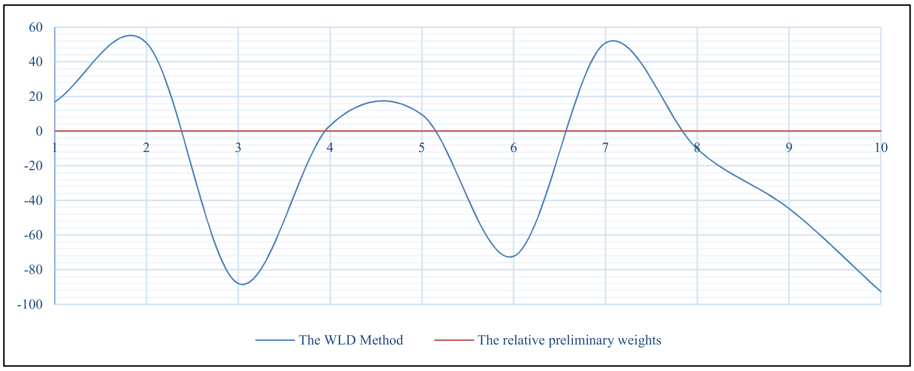

Fig. 16. Variation range between weights resulted from WLD method and relative preliminary weights.

Fig. 13 reveals how the rankings could be potentially different if MCDM methods, except for RBOP, make use of applying preliminary weights given by DM.

6.3. Limitations

RBOP and WLD are designed to offer the decision-making process outputs in line with what DM(s) expect and desire. It does not necessarily mean that DM(s) aim to opt for one specific alternative or consider a group of alternatives as to the most potential candidates, it implies that DM(s) have considered some ideal concepts for each alternative and also an optimal ideal alternative for the entire problem as the best alternative in their minds. The words of expectation and desire connote the relative knowledge of DM(s) regarding the problem and its components including the alternatives and importance weight of criteria.The main limitation emerges here; RBOP can be employed merely when DM(s) possess complete knowledge or relative understanding of the problem context and the problem data. Hence, in contrast to other conventional MCDM methods, RBOP can be applied solely when there are such aforementioned circumstances.

The new form of RBOP is dealing with another limitation. As opposed to this paper's problem in which we have complete information about its data assessment due to the expertise we have, RBOP with crisp numbers can be only exercised when the problem deals with the least linguistic variables to express the relation between the alternatives and criteria. Various decision-making problems' variables are only dealing with the crisp data *e.g.*, melting point, electrical resistance and conductance, etc., for the material selection problem, real-time price, distance from the marketplace, etc., for the facility location selection problem. Therefore, in dealing with the problems that involve with linguist variables, the grey form of RBOP needs to be utilized.

7. Conclusion and future research

In this supplier evaluation case, the hypermarket owners desire to select rank the alternatives in accordance with their desires, while, they have complete information about the evaluation criteria and the cheese suppliers. Therefore, to achieve the mentioned aim, in the article, a new form of RBOP with crisp value has been proposed to solve this problem as a complex (MCDM) problem. Alongside the new form of RBOP, we introduced the developed form of a new MCDM weighting method called WLD method. Both new methods have been architected based on the human behavioural pattern in the decision-making process. In contrast to other MCDM methods, by make use of optimal alternative and optimum alternatives, RBOP tries to find the best alternative in accordance with what DMs most desire. On the other hand, as a subjective weighting method, by using a combination approach of DM's decisions and pairwise comparison, the WLD method simulates the criteria analysis process performed by DM in its algorithm to compute the ultimate weights which are directly derived from the DMs' mind. Both methods are used when perfect information is available to the DMs about the problem including the alternatives and criteria. In the supplier evaluation/selection cases, or, in general, all MCDM problems, both methods possess salient advantages than other MCDM methods. The typical MCDM methods use various approaches, algorithms, and philosophies to derive the best alternatives from decision matrix without consideration of the external forces' impacts except for the impact of weights obtained from DMs' comments in some cases; while RBOP utilizes other philosophy. As external forces, RBOP considers the impact of the optimum and optimal alternative in which they have an independent existence outside of the decision matrix. In line with it, the comparisons performed in the paper showed that RBOP results are different from other MCDM methods, which shows that most MCDM results are not what DMs desire about the final product. Also, comparing to other subjective methods such as AHP and BWM, the WLD method benefits from a simpler algorithm and derives the more accurate weights than the

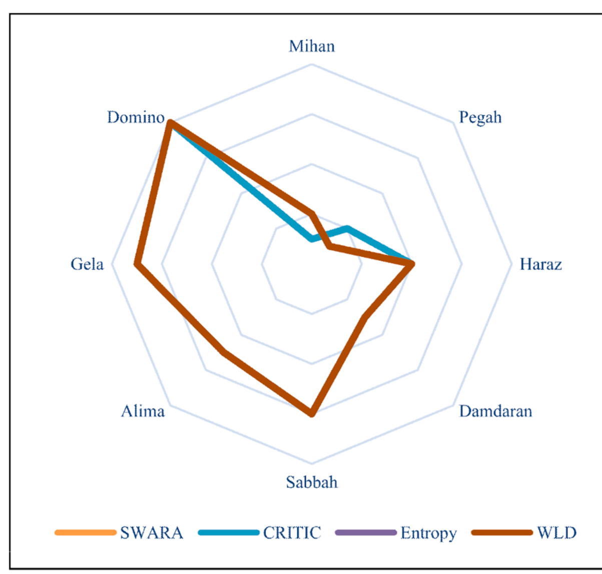

Fig. 17. Supplier rankings using different weighting methods.

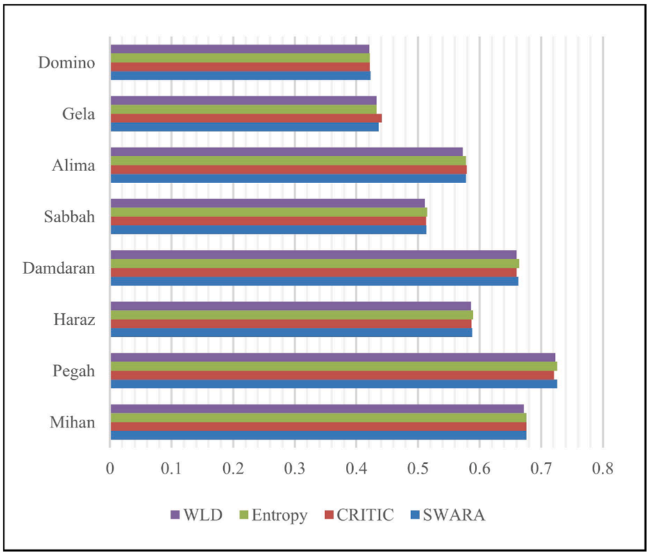

Fig. 18. Final scores of suppliers using different weighting methods.

mentioned methods by providing a platform for DM to revise his/her decisions in the two-phase algorithm. To compute ultimate weights which pictures a clear image of what DM thinks and determines, in the algorithm, the weights that are originated from the DM's previous experiences (see Fig. 6, Feedback/ information for judgment of another case) combine with the weights that are derived from the pairwise comparison (where DM faces the problem's alternatives and criteria). WLD has great advantages that make it an interesting method to use to solving MCDM problem:

1) The WLD number of comparisons is equal to AHP and more than BWM, nevertheless, in contrast to the BWM and AHP complex algorithms, it uses a simple algorithm that makes it very simple to implement and operate. Moreover, using the concepts of win, loss, and draw is very understandable which increases the decision-making accuracy.
2) The WLD's products are more reliable than the other weighting methods. One of the lacks that objective methods are suffering from is inaccuracy in the methods' final products which causes by the ignorance of the DM's interference in the weights computing process. On the other side of the coin, when complete/partly information is available, the subjective methods' performances are based on DM's interference in the computation process to cover the lack of objective methods. However, the popular subjective methods e.g. AHP, ANP, and BWM solely use DM's cooperation once, while, WLD provides a platform that empowers DM to modify his/her decisions which make the eventuated weights more reliable.
3) In WLD method, DM expresses his/her opinions solely once (without consideration of the number's texture), and only deals with linguistic concepts (not variable) in the comparison process which is making it much easier to use than other methods.
4) In addition to the computation of criteria' weights independently, WLD also can be integrated with other MCDM weighting subjective and objective methods.

Both proposed methods are constituted based on the human behavioural pattern. Both try to make results closer to what DM desires. We suggest the application of both methods in behavioural decision-making problems. Improving the structure of using optimum and optimal points in the RBOP based on the different human behavioural patter would be another suggestion for future research. To assess the adaptability of the novel methods and validity of their results, it would be interesting to apply them on the other MCDM problems and evaluate the results with the field research and experimental research. The WLD algorithm is easy to integrate with other MCDM weighting methods. We suggest developing both methods to embrace group decision-making by involving more than one DM. We suggest the integration of the WLD method with the objective methods e.g., Shannon's entropy to solve MCDM problems and cover their lack of accuracy. So far, along with the crisp numbers, RBOP is developed under the grey environment. Therefore, developing the fuzzy form of both methods is another suggestion for future research. Furthermore, using the incorporation of fuzzy methods to deal with the uncertainty associated with the proposed scale for transforming the qualitative linguistic variables to quantitative variables would be another suggestion for future work. Finally, we suggest the application of RBOP and WLD to the design of collaborative-networked organisations. Indeed, extending the methods to solve the partner selection problem brought by Andres, Poler, Camarinha-Matos, and Afsarmanesh (2017) would be an interesting suggestion for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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