A comparison of TOPSIS, grey relational analysis and COPRAS methods for machine selection problem in the food industry of Turkey

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Abstract: The paper aims to compare the results of the selection/choice of cream separators by using multi-criteria decision-making methods in an integrated manner for an enterprise with a dairy processing capacity of 80 to 100 tons per day operating in the Turkish food sector. A total of 7 alternative products and 7 criteria for milk processing were determined. Criterion weights were calculated using entropy method and then integrated into TOPSIS (Technique for Order Preference by Similarity to Ideal Solutions), GRA (Grey Relational Analysis) and COPRAS (Complex Proportional Assessment) methods. Sensitivity analyses were carried out on the results obtained from the three methods to check for their reliability. At the end of the study, similar alternative and appropriate results were found from the TOPSIS and COPRAS methods. However, different alternative but appropriate or suitable results were obtained from the GRA method. Sensitivity analysis of the three methods showed that all the methods used were valid. In the review of available and related literature, very few studies on machine selection in the dairy and food sector in general were found. For this reason, it is thought that the study will contribute to the decision-making process of companies in the dairy sector in their choice of machinery selections. As far as is known, this paper is the first attempt in extant literature to compare in an integrated manner the results of TOPSIS, COPRAS and GRA methods considered in the study.

Key words: machine selection, decision making, TOPSIS, grey relational analysis, COPRAS.

1. Introduction

National or international manufacturing companies are investing heavily in their product portfolios so as to be successful in highly competitive markets. Companies make these investments not only to enter new markets, but also to transform or rejuvenate already existing markets within which they serve. This is important because it is vital for manufacturing companies to develop their skills to survive fierce competition from other competitors. In order for manufacturing companies to achieve this, they must work with the right machines. However, choosing the right machine is always critical, difficult and complex (Aloini *et al.*, 2014). Choosing an unsuitable

or inappropriate machine will negatively affect the entire production system. Owing to this, selecting a suitable machine for a particular production system is vital for the sustainability of the entire production system. In addition, outputs of the production system such as ratio, quality and cost are generally directly proportional to the choice of machine selected and applied in the production system (Ayağ and Özdemir, 2006). Since the cost of investment in machinery is a huge burden on companies, they are very sensitive and careful in their choice of machine to spend on. Today, the tendency of companies to make evaluations based on scientific methods instead of making intuitive decisions with only knowledge and experience is increasing rapidly. In recent years,

companies have been using multi-criteria decision-making methods, with its inherently complex structures, for machine selection decisions. Multi-criteria decision-making can generally be defined as a collection of methods used to choose, sort or classify two or more alternatives, taking into account the quantitative and/or qualitative criteria that often conflict each other.

According to the 2019 dairy market research published by The United Nations Food and Agriculture Organization (United Nations FAO), in 2018 global milk production in India, Turkey, the European Union, Pakistan, the United States and due to production expansions in Argentina, reached 843 million tons which represents an increment of 2.2% compared to 2017. The report also emphasized the widespread use of integrated dairy production systems in Turkey as one of the reasons for the increased productivity.

According to the Organization for Economic Cooperation and Development (OECD) and FAO's 2019 Agricultural Outlook, the experienced increase in dairy production is estimated to reach 981 million tons by 2028 at an increasing rate of 1.7%. The increase in production is directly related to the increase in consumption. Again, in the report of OECD and FAO, milk consumption is predicted to increase by more than 1%. According to estimates from FAO's 2019 Food Outlook report, Turkey with an estimated production output of about 24 million tons is ranked 8th on the world dairy production ranking. Accordingly, it is possible to say that both national and international dairy processing plants in Turkey occupy an important position in the international dairy processing competition.

The study aimed to compare the different MCDM methods considered to solve problems of selecting cream separator for a plant with dairy processing capacity of 80 to 100 tons per day operating in Turkey. The cream separator is used in the standardization phase, which is one of the most important stages in dairy pre-processing. In the standardization phase, milk is separated into two forms as cream and skimmed milk (Chandan, 2008). The separated cream and skimmed milk are processed according to the oil content of other products produced in the facility. For the purpose of this study, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solutions), GRA (Grey Relational Analysis) and COPRAS (Complex Proportional Assessment) methods were selected due to the similarities in the

basic underlying ideas of these methods. However, GRA method was preferred in the normalization process as it has a different approach compared to the other two methods.

In the second section of the study is the review of the relevant literature in relation to the study and brief information about the methods used in the analysis is provided in the third section. Analysis made within the scope of the study are included in the fourth section and the results of the analysis are evaluated in the conclusion section.

2. Literature review

There are many studies in the literature on using multi-criteria decision making (MCDM) methods to determine the choice of machine selections. When these studies are examined, it is possible to see that machine selection problems in different sectors are addressed. On the one hand, earlier studies (Özgen *et al.*, 2011; Kumru and Kumru 2015; Özceylan *et al.*, 2016; Wu *et al.*, 2016; Kabak and Dağdeviren, 2017; Camcı *et al.*, 2018) confirm that companies operating in the manufacturing sector have benefited from MCDM methods for various machine selection problems. On the other hand, some other studies (Clarke *et al.*, 1990; Samanta *et al.*, 2002, Alpay and Ihpar, 2018; Štirbanović *et al.*, 2019) also provided evidence that MCDM techniques are applied in the selection of machines used in the mining industry.

Ulubeyli and Kazaz (2009), Yazdani-Chamzini and Yakhchali (2012), Temiz and Çalış (2017) and Uğur (2017) demonstrated usage of MCDM methods in the construction industry. Similarly Ertuğrul and Güneş (2007), Vatansever and Kazançoğlu (2014), and Ertuğrul and Öztaş (2015) also showed that the method is preferred in solving machine selection problems in the textile industry. Aloini *et al.* (2014), Özdağoğlu *et al.* (2017) and Çakır (2018) evaluated the machine selection decisions of companies operating in different areas within the food industry using MCDM methods. In addition, prior studies (Yılmaz and Dağdeviren, 2010, 2011; Paramasivam *et al.*, 2011; Taha and Rostam, 2011; Datta *et al.*, 2013; Karim and Karmaker, 2016) also used different MCDM methods for the selection of machines with applicability in more than one sector.

Very few studies addressing multi-criteria decision making methods not only for machine selection problems but also in other areas in the food sector

can be found. For instance, Gurmeric *et al.* (2013) investigated multi-criteria decision making methods in determining the optimum aroma level in terms of vanilla, strawberry and cocoa for prebiotic pudding. Karaman *et al.* (2014) also using multi-criteria decision making methods considered the evaluation of different ratios of ice cream mixes in terms of physicochemical, bioactive and sensory terms. In a similar study, Ozturk *et al.* (2014) also applied multi-criteria decision making methods to determine physiochemical properties of the mixtures in mellorine dessert and the functional and sensory properties of mellorine enriched with vegetable juices in different concentrations. Doğan *et al.* (2016) used multi-criteria decision making techniques in determining the fat content in hot chocolate and increasing the biofunctional properties of butter using fiber concentrates.

3. Methodology

The presence of more than one criterion in MCDM problems causes different perspectives and complex information to emerge. The main purpose of the MCDM method is to help decision makers organize and synthesize such information more comfortably in decision making, to minimize the potential for post-decision remorse by being satisfied with all criteria (Belton and Stewart, 2002). Many methods have been developed for solving multi-criteria decision making problems. Brief information about the methods considered in this study is presented below.

1.1 Weighting with entropy method

The entropy method is expressed as a measure of uncertainty about a random variable (Zhang *et al.*, 2011). The primary steps of the entropy method can be briefly described as follows (Deng *et al.*, 2000).

1: Each criterion in the decision matrix in Equation (1) is normalized as specified in Equation (2).

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} \\ x_{21} & x_{22} & \cdots & x_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} \end{bmatrix} \tag{1}$$

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \quad i = 1, 2, ., n; j = 1, 2, ., m \tag{2}$$

In Equation (2), xij denotes the real value of each alternative, while pij denotes the normalized form values for each criterion. A normalized decision matrix in the shape of the equation specified below is obtained after solving Equation (2).

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1j} \\ p_{21} & p_{22} & \cdots & p_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ p_{i1} & p_{i2} & \cdots & p_{ij} \end{bmatrix} \tag{3}$$

2: In the light of information contained in the normalized decision matrix in Equation (3), entropy values (e_j) for each criterion are calculated using Equation (4) as specified as follows.

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{4}$$

In Equation (4), k is calculated as 1/ln(n) and is a constant which guarantees $0 \leq e_j \leq 1$. In Equation (4), ej denotes the amount of information for a certain criterion. When the entropy value is smaller, then the importance of the criterion on decision making process becomes higher (Wu *et al.*, 2011). In other words, entropy value shows the uncertainty of information on a criterion. The uncertainty decreases when the information values for the criteria are close to each other. Therefore, the entropy value takes a small value accordingly.

3: The degree of divergence (d_j) of the average information contained in each criterion can be calculated as follows:

$$d_j = 1 - e_j \tag{5}$$

The degree of differentiation (d_j) refers to the contrast intensity of the information in the criterion. Accordingly, as the value of the d_j criterion increases, the importance of the criterion in problem solving increases (Wang and Lee, 2009). In other words, it is the degree of difference between the information belonging to the criteria. It has an inverse relationship with its entropy value.

4: The last stage in the entropy method is where criterion weights are calculated. This calculation can be accomplished in Equation (6):

$$w_j = \frac{1 - e_j}{\sum_{i=1}^{n} 1 - e_j} \tag{6}$$

In Equation (6), w_j shows the weight values of the criteria. The important point to be considered here is the rule that the sum of all w_j values ($w_1 + w_2 + \ldots + w_n$) should be equal to 1.

3.1. TOPSIS method

Hwang and Yoon (1980) developed the TOPSIS method based on the concept that the chosen alternative should have the shortest possible distance from the positive ideal solution and the farthest distance away from the negative ideal solution. The steps of the TOPSIS method (Seçme *et al.*, 2009) are briefly presented below.

1: The decision matrix is normalized using Equation (7).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{J} x_{ij}^2}} \quad j=1, 2, \ldots, J; i=1, 2, \ldots, n \quad (7)$$

In Equation (7), r_{ij} captures the normalized value and i in x_{ij} is the numerical value of the alternative in accordance to the criteria j.

2: A weighted normalized decision matrix is obtained by multiplying the normalized matrix by the weights of the criteria (w_j).

$$v_{ij} = w_j^* \times r_{ij} \quad j=1, 2, \ldots, J; i=1, 2, \ldots, n \quad (8)$$

3: Ideal solution (maximum value, A^*) and negative ideal solution (minimum value, A^-) are determined.

$$A^* = \{v_1^*, v_2^*, \ldots, v_3^*\} \quad (9)$$

$$A^- = \{v_1^-, v_2^-, \ldots, v_3^-\} \quad (10)$$

4: The distance between each alternative is calculated by using n-dimensional Euclidean distance as

$$d_i^* = \sqrt{\sum_{j=1}^{J} (v_{ij} - v_i^*)^2}, \quad j=1, 2, \ldots, J \quad (11)$$

$$d_i^- = \sqrt{\sum_{j=1}^{J} (v_{ij} - v_i^-)^2}, \quad j=1, 2, \ldots, J \quad (12)$$

where, d_i^* symbolizes the positive ideal separation measure and d_i^- symbolizes the negative ideal separation measure.

5: The closeness coefficient (CCi) of each alternative is calculated with the following equation:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \quad (13)$$

6: At the end of the analysis, the alternatives are ranked by comparing the CCi values and subsequently a decision is made.

In the last step, the calculated CCi values are listed in ascending order. The alternatives are ranked such that the alternative with the largest CCi value is the optimum alternative.

3.2. GRA method

GRA is a method of analysis that measures the relationship among matrix elements based on the difference of similarity or difference of development trends among these elements (Feng and Wang, 2000). The calculation procedures and steps of the GRA method can be described as follows (Wu and Peng, 2016).

1: After the decision matrix is created as in Equation (1), the series that make up the matrix in the decision problem with i rows (i=1, 2, …, m) and j columns (j=1, 2,…, n), according to the status of benefit, cost and nominality is normalized as follows.

Benefit-oriented criterion: If the criterion in the series has the property "the larger value is better", the i, rows (i=1, 2,…, M) and j, the columns (j=1, 2,…, n) the following normalization procedure is applied.

$$x_{ij}' = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (14)$$

Cost-oriented criterion: If the criterion in the series has the property "the smaller value is better", i, rows (i = 1, 2,…, M) and j columns (j = 1, 2,…, n) the following normalization procedure is applied.

$$x_{ij}' = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (15)$$

Nominality criterion: If the criterion in the series has a value such as x_{0b} (ie if it has the property "the nominal value is better") The following normalization procedure is applied to i lines (i = 1, 2,… columns, m) and j (j = 1, 2,…, n) columns.

$$x_{ij}' = 1 - \frac{|x_{ij} - x_{0b}|}{\max\{\max_i x_{ij} - x_{0b}; x_{0b} - \min_i x_{ij}\}} \quad (16)$$

At the end of the calculation processes and steps, a normalized matrix of the form specified below is obtained.

$$R' = \begin{bmatrix} x'_{11} & x'_{12} & \cdots & x'_{1j} \\ x'_{21} & x'_{22} & \cdots & x'_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ x'_{i1} & x'_{i2} & \cdots & x'_{ij} \end{bmatrix} \qquad (17)$$

2: For each criterion, a reference is determined using the normalization matrix x'(0).

$$x'(0) = \left(x'_{11}(0), x'_{12}(0), x'_{13}(0),..., x'_{1j}(0) \right) \qquad (18)$$

In Equation (18), $x'_{1j}(0)$ expresses the jth reference value and for each criteria it is obtained by the largest normalization value.

3: The difference $\Delta_{ij}(0)$ between the reference series x'(0) and normalized values is calculated using Equation (19) and as in Equation (20), an absolute value matrix is created.

$$\Delta_{ij}(0) = |x'(0) - x'_{ij}| \qquad (19)$$

$$\Delta = \begin{bmatrix} \Delta_{11}(0) & \Delta_{12}(0) & \cdots & \Delta_{1j}(0) \\ \Delta_{21}(0) & \Delta_{22}(0) & \cdots & \Delta_{2j}(0) \\ \cdots & \cdots & \cdots & \cdots \\ \Delta_{i1}(0) & \Delta_{i2}(0) & \cdots & \Delta_{ij}(0) \end{bmatrix} \qquad (20)$$

4: The grey relational coefficients $\gamma_{ij}(0)$ are calculated with the help of the equation specified below in accordance to the absolute value matrix.

$$\gamma_{ij}(0) = \frac{\min\limits_{i}\min\limits_{j} \Delta_{ij}(0) + \delta\max\limits_{i}\max\limits_{j} \Delta_{ij}(0)}{\Delta_{ij}(0) + \delta\max\limits_{i}\max\limits_{j} \Delta_{ij}(0)} \qquad (21)$$

where δ is expressed as the distinguished coefficient. $\delta \in [0,1]$ bound, however, it is generally accepted to be 0.5.

5: With the help of the Equation (22), the grey relational degrees (Γ_i) are calculated.

$$\Gamma_i = \sum_{j=1}^{n} \left(w_j \times \gamma_{ij}(0) \right) \text{ subject to } \sum_{j=1}^{n} w_j = 1 \qquad (22)$$

w_j in Equation (22) indicates the weight of the jth criterion. The condition in the equation states that the sum of the weights of all criteria should be 1.

The grey relationship degrees obtained as a result of Equation (22) are ranked in descending order and the alternative with the greatest grey relationship degree is determined as the optimum alternative.

3.3. COPRAS method

An examination of the basic underlying idea of the COPRAS method where preference for alternatives are based on ideal and negative ideal solutions can be thought of as similar to that of the TOPSIS method (Feizabadi *et al.*, 2017). The calculation steps of the COPRAS method can generally be explained as follows (Zavadskas *et al.*, 2004):

1: Creation of weighted normalized decision making matrix.

$$d_{ij} = \frac{w_j x_{ij}}{\sum_{i=1}^{n} x_{ij}} \qquad (23)$$

where w_j in Equation (23) represents the weight of the j criterion.

2: Weighted normalized indices are summed up. At this stage, the maximization S_{+j} or minimization S_{-j} aspects of the criteria are taken into account. Index totals, m; to show the number of criteria are calculated as follows.

$$S_{+j} = \sum_{i=1}^{m} d_{+ij} \quad \text{and} \quad S_{-j} = \sum_{i=1}^{m} d_{-ij} \qquad (24)$$

3: Relative significance values of alternatives (Q_i), S_{-min}; minimum S_{-j} is obtained with the help of the following equation.

$$Q_i = S_{+j} + \frac{S_{-min} \sum_{j=1}^{n} S_{-j}}{S_{-j} \sum_{j=1}^{n} \frac{S_{-min}}{S_{-j}}} \qquad (25)$$

Alternatives are then ranked according to their relative significance. The alternative of highest relative importance is determined as the optimum alternative.

4. Results

In addressing the decision problem, first, the most important criteria to consider when choosing a cream separator were determined. In this context, a total of 20 companies engaged in the manufacturing of cream separator in Turkey were selected. Sales managers of the selected companies were contacted via e-mail and/or phone call and feedback was received from a total of 9 companies. The criteria were created by blending both criteria presented by the sales managers and the opinions of the production manager of the dairy processing plant. In this way, 7 criteria were

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determined: cream separation performance (C_1), drum discharge volume (C_2), drum turnover (C_3), energy consumption (C_4), weight (C_5), price (C_6) and number of cream separators (C_7).

After determining the criteria proposals were sent to cream separator manufacturing firms in Turkey and also to the nine firms from whom feedbacks were received requesting for cream separators in their product portfolios. In the portfolios, offers for 7 alternative machines from 5 companies that have cream separators suitable for application in their dairy processing plant were submitted. The offers received and the features of the cream separator in the portfolio of the suppliers are summarized in Table 1.

4.1. Calculation of criterion weights by entropy method

Entropy method was used to determine the criterion weights. Calculation of the criterion weights by the entropy method enables more reliable results by using objective weightings instead of weighting criteria subjectively. The criteria weights obtained from calculations using the entropy method were presented in Table 2.

A thorough look at the criterion weights reveals that the most important criterion in choosing cream separator is C_2, drum discharge volume, criterion with a weight of 34.42%. This criterion is followed by C_6 with a weight of 21.48%, C_7 with a weight of 16.72% and C_1 with a weight of 11.86%. In the ranking of criterion weights, the last three criteria were C_4 with a weight of 8.6%, C_5 with a weight of 3.68% and C_3 with a weight of 3.23%.

Table 1. Alternatives and their associated Properties According to Criteria (Decision Matrix).

Alternatives	Criteria						
	C_1	C_2	C_3	C_4	C_5	C_6	C_7
	(+)	(+)	(+)	(-)	(-)	(-)	(-)
A_1	10	3.5	7.7	15	1.3	39	2
A_2	20	6	6.8	20	1.6	65	1
A_3	15	9	5.05	30	1.6	60	2
A_4	18	15	6.2	18.5	1.3	68	1
A_5	10	15	5.7	18.5	1.5	87	2
A_6	20	18	6.2	18.5	1.8	120	1
A_7	12.5	15	5.1	15	1.1	42	2

Criteria with (+) sign have beneficial characteristics while those with the (-) sign are determined as criteria with cost characteristics.

Table 2. Criterion Weights Calculated by Entropy Method.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
W_i	0.1186	0.3442	0.0323	0.086	0.0368	0.2148	0.1672

4.2. Calculations by TOPSIS method

TOPSIS method was initially used to sort the alternatives taken from cream separator suppliers for the dairy processing plant where the application was made and to make the final decision. The criteria contained in the decision matrix as shown in Table 1 were calculated using TOPSIS method the results the calculation processes are presented in the tables below. In the first stage of the TOPSIS calculation process, data collected from different sources were normalized using Equation (7). Then, normalized weighted values were calculated by multiplying the normalized values by the criterion weights using Equation (8). In the next stage of the TOPSIS method, ideal (A^*) and negative ideal (A^-) solutions were determined with elements in the weighted normalized decision matrix, depending on whether the criteria were of benefit or cost oriented. After this calculation process, the n-dimensional Euclidean distance between each alternative was calculated using Equation (11) and Equation (12) following that positive separation (d^*) and negative separation (d^-) measurements were determined.

Table 3. Normalized Values in TOPSIS Method.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.2422	0.1042	0.4718	0.2847	0.3334	0.2009	0.4588
A_2	0.4843	0.1786	0.4166	0.3795	0.4104	0.3348	0.2294
A_3	0.3632	0.2679	0.3094	0.5693	0.4104	0.3090	0.4588
A_4	0.4359	0.4466	0.3799	0.3511	0.3334	0.3502	0.2294
A_5	0.2422	0.4466	0.3492	0.3511	0.3847	0.4481	0.4588
A_6	0.4843	0.5359	0.3799	0.3511	0.4617	0.6180	0.2294
A_7	0.3027	0.4466	0.3125	0.2847	0.2821	0.2163	0.4588

Table 4. Weighted Normalized Values in TOPSIS Method.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.0287	0.0359	0.0152	0.0245	0.0123	0.0432	0.0767
A_2	0.0574	0.0615	0.0135	0.0327	0.0151	0.0719	0.0384
A_3	0.0431	0.0922	0.0100	0.0490	0.0151	0.0664	0.0767
A_4	0.0517	0.1537	0.0123	0.0302	0.0123	0.0752	0.0384
A_5	0.0287	0.1537	0.0113	0.0302	0.0142	0.0963	0.0767
A_6	0.0574	0.1844	0.0123	0.0302	0.0170	0.1328	0.0384
A_7	0.0359	0.1537	0.0101	0.0245	0.0104	0.0465	0.0767

Table 5. Ideal (A*) and Negative (A⁻) Ideal Solution Values in TOPSIS Method.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A*	0.0574	0.1844	0.0152	0.0245	0.0104	0.0432	0.0384
A⁻	0.0287	0.0359	0.0100	0.0490	0.0170	0.1328	0.0767

Table 6. Positive (d*) and Negative (d⁻) Separation Measures in TOPSIS Method.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
d*	0.0574	0.1844	0.0152	0.0245	0.0104	0.0432	0.0384
d⁻	0.0287	0.0359	0.0100	0.0490	0.0170	0.1328	0.0767

4.3. Calculations by GRA method

In the GRA method normalisation processes are just as those observed in the TOPSIS method. However, in addition to the purpose of normalizing the data collected from different sources, it was more convenient to normalize the data after standardizing data in a small range since the elements in the decision matrix were values drawn from data in wide ranges. Normalization processes in the GRA method were carried out with Equation (14) and Equation (15). After the normalization matrix was obtained, the reference series and absolute value matrix were created with the help of Equation (18) in accordance with the benefit or cost characteristics of the criteria.

After this calculation process, the GRA relational coefficients matrix was calculated with the help of Equation (21). In this calculation process, the separator coefficient (δ) was taken as 0.5, as in many other studies in the literature (Tosun, 2006; Sharma and Yadava, 2011; Guo and Sun, 2016; Sun, 2014). The results of the calculations made by the GRA method are presented in Table 7 to Table 9 as shown below.

Table 7. Normalization Values in GRA Method.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.0000	0.0000	1.0000	1.0000	0.7143	1.0000	0.0000
A_2	1.0000	0.1724	0.6604	0.6667	0.2857	0.6790	1.0000
A_3	0.5000	0.3793	0.0000	0.0000	0.2857	0.7407	0.0000
A_4	0.8000	0.7931	0.4340	0.7667	0.7143	0.6420	1.0000
A_5	0.0000	0.7931	0.2453	0.7667	0.4286	0.4074	0.0000
A_6	1.0000	1.0000	0.4340	0.7667	0.0000	0.0000	1.0000
A_7	0.2500	0.7931	0.0189	1.0000	1.0000	0.9630	0.0000

Table 8. Reference Series and Absolute Value Table in GRA Method.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	1.0000	1.0000	0.0000	1.0000	0.7143	1.0000	0.0000
A_2	0.0000	0.8276	0.3396	0.6667	0.2857	0.6790	1.0000
A_3	0.5000	0.6207	1.0000	0.0000	0.2857	0.7407	0.0000
A_4	0.2000	0.2069	0.5660	0.7667	0.7143	0.6420	1.0000
A_5	1.0000	0.2069	0.7547	0.7667	0.4286	0.4074	0.0000
A_6	0.0000	0.0000	0.5660	0.7667	0.0000	0.0000	1.0000
A_7	0.7500	0.2069	0.9811	1.0000	1.0000	0.9630	0.0000

Table 9. GRA Relational Coefficients Matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.0395	0.1147	0.0323	0.0287	0.0152	0.3333	1.0000
A_2	0.1186	0.1296	0.0192	0.0369	0.0234	0.4241	0.3333
A_3	0.0593	0.1535	0.0108	0.0860	0.0234	0.4030	1.0000
A_4	0.0847	0.2434	0.0151	0.0340	0.0152	0.4378	0.3333
A_5	0.0395	0.2434	0.0129	0.0340	0.0198	0.5510	1.0000
A_6	0.1186	0.3442	0.0151	0.0340	0.0368	1.0000	0.3333
A_7	0.0474	0.2434	0.0109	0.0287	0.0123	0.3418	1.0000

Finally, the grey relation degrees (Γ_i) are calculated and presented in Table 11 along with the results of other methods.

4.4. Calculations by COPRAS method

In relation to the purpose of the study, the results obtained with the COPRAS method were found as follows. The first step in COPRAS application is the creation of a weighted normalized matrix. The weighted normalized matrix created as a result of the calculations made with the COPRAS method applied in the study is given in Table 10.

Table 10. Weighted Normalized Values in COPRAS Method.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.0112	0.0148	0.0058	0.0095	0.0047	0.0174	0.0304
A_2	0.0225	0.0253	0.0051	0.0127	0.0058	0.0290	0.0152
A_3	0.0169	0.0380	0.0038	0.0190	0.0058	0.0268	0.0304
A_4	0.0202	0.0633	0.0047	0.0117	0.0047	0.0304	0.0152
A_5	0.0112	0.0633	0.0043	0.0117	0.0054	0.0389	0.0304
A_6	0.0225	0.0760	0.0047	0.0117	0.0065	0.0536	0.0152
A_7	0.0141	0.0633	0.0039	0.0095	0.0040	0.0188	0.0304

After the normalization process, weighted normalized indexes (S_{+j} and S_{-j}) were summed according to the maximization and minimization criteria and

the relative importance (Q_i) of the alternatives was calculated. Q_i values as well as the ranked order of alternatives are presented in Table 11.

4.5. Ranking of alternatives

The closeness coefficients calculated according to the three methods used in the study, their grey relational degrees, their relative importance and the ranked order of the alternatives accordingly are summarized in Table 11 below.
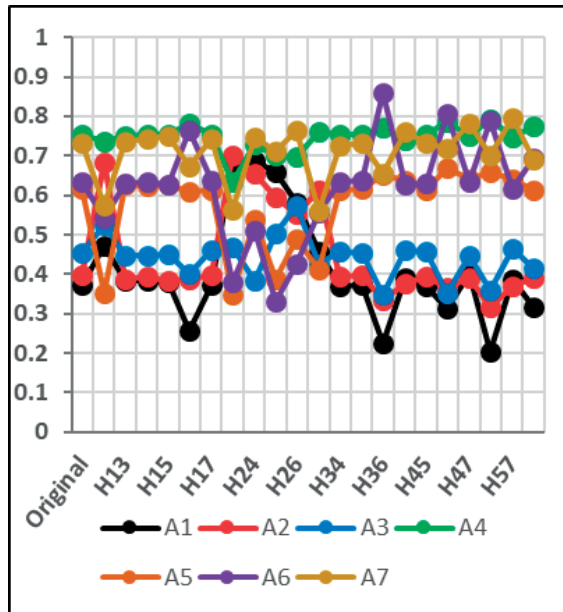
Table 11. CCi Values and Ranked Alternatives in TOPSIS Method.

	TOPSIS		GRA		COPRAS	
	CC_i	Sıralama	Γ_i	Sıralama	Q_i	Sıralama
A_1	0.3738	7	0.4692	7	0.1137	7
A_2	0.3968	6	0.4746	6	0.1340	6
A_3	0.4529	5	0.5869	3	0.1206	5
A_4	0.7554	1	0.5422	5	0.1702	1
A_5	0.6146	4	0.6352	2	0.1377	4
A_6	0.6357	3	0.8193	1	0.1615	3
A_7	0.7331	2	0.5834	4	0.1623	2

At the end of the analysis of TOPSIS and COPRAS, it was concluded that the most suitable cream separator for a facility with a dairy processing capacity of 80 to 100 tons per day is the A_4 alternative. The order of other alternatives is in the form $A_4 > A_7 > A_6 > A_5 > A_3 > A_2 > A_1$. The result of GRA method demonstrated that the most suitable cream separator is the A_6 alternative. The order of other alternatives following the GRA method is of the form $A_6 > A_5 > A_3 > A_7 > A_4 > A_2 > A_1$.
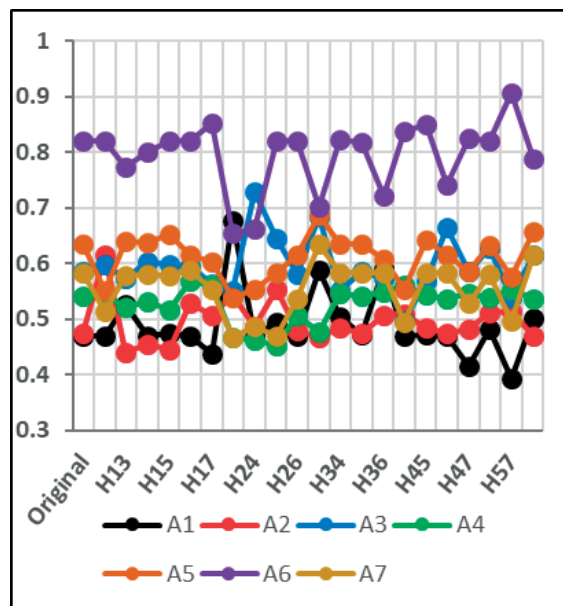
4.6. Sensitivity analysis

In order to analyze the sensitivity of the results, the binary replacement method as used in the literature by Önüt *et al.* (2009), Kang *et al.* (2012), Pang and Bai (2013), Nguyen *et al.* (2014), Ahmed *et al.* (2019) was used. Alternative sequences obtained by changing the weights of each criterion were examined. With a total number of 7 criteria and pairwise comparisons, 21 $(7!/((7-2)! \times 2!))$ different results were calculated. The graphs obtained by changing the criterion weights are shown as follows:

When the sensitivity analysis graphs for TOPSIS and COPRAS methods are examined together, it can be seen that there are no serious variations in the ranking of the A_4 alternative. In Figure 4.2, when the part of the A_6 alternative is examined, it is seen that the order of the A_6 alternative is generally

Figure 4.1. Sensitivity Analysis of Alternatives According to TOPSIS Method.

Figure 4.2. Sensitivity Analysis of Alternatives According to GRA Method.

the same as the criteria weights change. With this result, it is possible to state that the most suitable alternative found using the GRA method is valid. When the results of the sensitivity analysis are evaluated together, it is possible to say that the results obtained for all three methods are consistent within themselves.
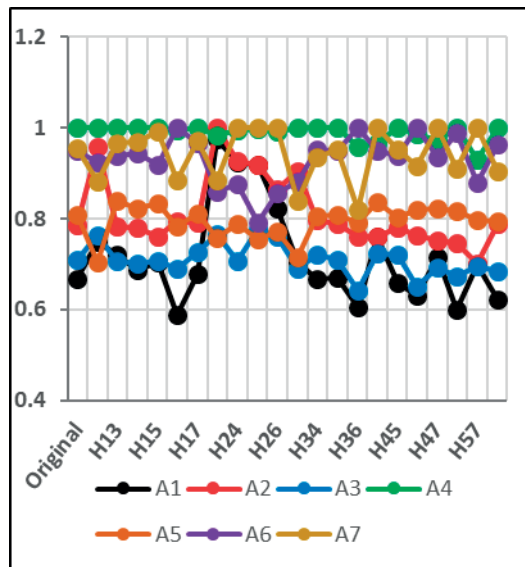
Figure 4.3. Sensitivity Analysis of Alternatives According to COPRAS Method.

5. Conclusion

Alternative is the most suitable alternative according to TOPSIS and COPRAS methods, however, the most suitable alternative in the GRA method is A_6. Differences in normalization processes can be thought of as the main reason why the results found with the GRA method are different from the results found with the TOPSIS and COPRAS methods. The TOPSIS method is heavily influenced by the choice of normalization techniques used (Pavličić, 2001; Shih *et al*., 2007; Çelen, 2014; Vafaei et al., 2018). In addition, study conducted by Chatterjee and Chakraborty (2014) demonstrated that the two methods operate with different normalization techniques and pointed that out as the reason for TOPSIS and GRA techniques giving different results. While the TOPSIS method uses the vector normalization technique, the GRA method operates with the max-min normalization technique, which is one of the linear normalization techniques. In addition, another reason why GRA and TOPSIS and COPRAS methods give different results is that GRA takes into account the criterion aspects (positive, negative, nominal) in the normalization process. Antucheviciene *et al*. (2012) stated that even if

the normalization methods affect the final ranking results, the results of TOPSIS and COPRAS methods are very close to each other. Stanujkic *et al*. (2013) explained this situation as being more affected by the criteria weights of both methods. Although TOPSIS and COPRAS methods use different normalization techniques, in both methods calculations are made on alternative results, unlike GRA, where calculations are made in the overlaps of alternatives.

A clear recommendation of cream separator for dairy processing plant as discussed within the scope of the study can be made in the light of the power of the results obtained from the analyses conducted. The main reason for this is that, it can be demonstrated to companies producing machinery for the dairy sector to produce machines according to customer demands and also to equip standard machines with similar technical features. However, considering the fact that TOPSIS and COPRAS methods take the alternatives into consideration, it can be said that A_4 alternative will be preferred. In such cases, it is suggested that experts' opinions be sought in the evaluation of the two alternatives. However, when the criteria discussed in the study are examined, it can be said that between A4 and A6 alternatives, A4 alternative is more suitable for the business. Drum speed, energy consumption and number of machines to be purchased are the same for both alternatives. It can be suggested that the results obtained by TOPSIS and COPRAS methods can be applied because the investment that the enterprise will make for the cream separator is a significant limitation for the enterprise. In this case, the advantage of TOPSIS and COPRAS methods will be used to evaluate over alternatives.

Apart from the criteria determined in this study, new applications of the methods such as recently proposed Range Target-based Criteria and Interval Data model of TOPSIS (Jahan *et al*. 2021) can be made for machine selection according to different technical features. However, the same technical features can be used by changing the methods used in the study. Also, AHP, SAW, expert opinion etc. techniques can be used to re-determined criteria weights and analyzes can be performed.

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