

New Grey Integrated Model to Solve a Machine Selection Problem for a Textile Company

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Abstract

The textile sector has become an indispensable part of the Turkish economy. The sewing machine is a long-lasting and easy-to-use tool widely used in the garment industry, which is a branch of the textile industry. The sewing machine is an indispensable production tool for the textile industry and sewing machine selection is a significant decision for the production performance of textile companies. Selecting an appropriate sewing machine increases production performance, while selecting an improper one reduces production performance. The sewing machine selection problem is a typical machine selection issue. Many criteria, such as cost, productivity, safety etc. are considered in the machine selection. Therefore, MCDM methods are applicable to solve the machine selection problem. This study develops an integrated grey MCDM model including Grey AHP and ROV-G to select the most appropriate sewing machine for an apparel textile company.

Key words: grey AHP, ROV-G, sewing machine selection, machine selection problem.

Introduction

Throughout the ages people have overcome many obstacles by creating solutions to hold onto their lives. For instance, when people did not have natural furs, they created various clothes to survive in cold climates. Over time, these clothes created a sector called 'textile'. The apparel industry is a branch of the textile sector. The output of this industry is delivered to the customer as ready-to-wear garments or household products. With the development of technology, they started to manufacture products in different fashion styles and shapes in this industry. In terms of exports and employment, the textile sector is extremely significant for the economy of Turkey [1]. According to May 2019 data, the share of exports of textiles and their raw materials in overall exports was 5.9% [2]. Only for May 2019, the total export volume of this sector was about 987 million dollars [2]. It can be said that the textile sector has become an indispensable part of the Turkish economy.

The sewing machine is a long-lasting and easy-to-use tool widely used in the garment industry. The history of the sewing machine is extremely long, with the first steel needle sewing machine trials dating back to the 1750s [1]. Sewing machines are used both individually and in the textile industry in the modern era. The sewing machine is an indispensable production tool for the textile industry and its selection is a significant decision for the production performance of textile companies. Selecting an appropriate sewing

machine increases production performance, while choosing an improper one reduces production performance. The selection of a sewing machine problem is a typical machine selection problem.

Machine selection is a significant decision for production performance and is a key element for the development of manufacturing systems. Due to considering many alternatives and conflicting objectives, as well as the lack of deep knowledge and experience of engineers and managers, the selection of an appropriate machine is a complex and time-consuming problem. Therefore, the decision maker should know the technological information required regarding machine properties for a proper and effective selection of an appropriate machine.

Many criteria, such as price, energy consumption, ergonomic suitability, productivity, compatibility with the system, and so on, should be considered while selecting a suitable machine. Thus, the machine selection problem can be handled as a multi criteria decision-making (MCDM) type. MCDM methods simplify the process of finding a solution and allow decision makers to achieve the right decisions [3]. This selection problem in the literature may be divided into two sub-problems: the selection of machine equipment (tool) and machine selection [4]. In the literature, MCDM methods have been used to solve both two sub-problems. For instance, Ayağ and Özdemir [5] combined the fuzzy analytic hierarchy process (AHP) and

Benefit/Cost (B/C) ratio analysis to select the best machine tool alternative. On the other hand, Aloini et al. [6] used peer intuitionistic fuzzy TOPSIS to evaluate and select packaging machines. Most of the studies used fuzzy methods, especially fuzzy AHP, to handle uncertainty in solving the machine selection problem. For example, Özgen et al. [7] proposed a hybrid model including DELPHI, fuzzy AHP and fuzzy PROMETHEE to select a pressing machine tool for a pipe clamp manufacturing company. Another attempt to solve the machine selection problem was by Taha and Rostam [8], who integrated fuzzy AHP and PROMETHEE to select a CNC turning centre machine. Dawal et al. [9] constructed a model including fuzzy AHP and fuzzy TOPSIS to evaluate and select machine tool alternatives. Another attempt by Nguyen et al. [10] proposed a model involving fuzzy AHP and fuzzy COPRAS to select a CNC machine tool.

The Fuzzy analytic network process (ANP), which is another fuzzy MCDM method, is also used to solve the machine selection problem. For instance, Ayağ and Özdemir used fuzzy ANP twice in solving a machine selection problem. One used only fuzzy ANP and another fuzzy ANP and fuzzy TOPSIS together for the machine selection problem [11-12]. Other studies also used fuzzy ANP to solve this selection problem [13-15].

There are many studies utilising fuzzy methods to evaluate and select a machine tool or machine alternatives. However, studies using grey numbers to solve the

machine selection problem are limited in the literature [4, 13, 16, 17]. Additionally, while crisp numbers cannot express human judgements or totally reflect real life condition, grey numbers can easily explain real life situations. Therefore, this study proposes a grey integrated model to solve the sewing machine selection problem. The study presents three contributions to literature. The first is to develop a new method which is called ROV-G (Grey Range of Value). The second is the first time in literature that the Grey AHP (analytic hierarchy process) and ROV-G methods have been used together to solve the sewing machine selection problem. In the literature, there are few studies [1,18] related to the sewing machine selection problem, and thus the third contribution of this study is to fill this research gap. The rest of this article is organised as follows: The steps of Grey AHP and ROV-G are presented in the methodology section. In the application section, the application of the grey integrated model in selecting a sewing machine for a textile company is indicated. In Section 4, a sensitivity analysis is presented. This article concludes with a brief conclusion and future research directions.

Methodology

In this study, a grey integrated model including Grey AHP and ROV-G was formulated to choose the most appropriate sewing machine for a textile company. The Grey AHP [19-22] method is used to determine the weights of criteria, and then ROV-G is used to evaluate the performance of sewing machine alternatives and to select the best one among them.

Crisp Range of Value (ROV)

Range of Value (ROV) was developed by Yakowitz et al. in 1993 [23]. The Crisp ROV method can be summarised as follows [24]:

Step 1: Structuring the decision matrix including alternatives and criteria.

$$X = (x_{de})_{l \times p} \quad d = 1, \dots, l \quad e = 1, \dots, p \quad (1)$$

Step 2: Normalising the decision matrix using **Equations (2)** (beneficial) and **(3)** (non-beneficial).

$$r_{de} = \frac{x_{de} - \min(x_{de})}{\max(x_{de}) - \min(x_{de})} \quad d = 1, \dots, l \quad e = 1, \dots, p \quad (2)$$

$$r_{de} = \frac{\max(x_{de}) - x_{de}}{\max(x_{de}) - \min(x_{de})} \quad d = 1, \dots, l \quad e = 1, \dots, p \quad (3)$$

Step 3: These normalised values are multiplied by the weights of criteria and summed to obtain the best and worst utility values as follows.

$$u_d^+ = \sum_{e=1}^p w_e \times r_{de} \quad d = 1, \dots, l \quad e = 1, \dots, p \quad (4)$$

$$u_d^- = \sum_{e=f+1}^p w_e \times r_{de} \quad d = 1, \dots, l \quad e = 1, \dots, p \quad (5)$$

Step 4: In the final step, utility values for each alternative are computed as:

$$u_d = \frac{u_d^+ + u_d^-}{2} \quad d = 1, \dots, l \quad e = 1, \dots, p \quad (6)$$

Crisp numbers are not sufficient to express human judgements in real life, thus grey numbers will be integrated with the ROV method in this study to reflect human judgements in real life.

Basic Mathematical Operations

In grey numbers, there are some mathematical operations, such as addition, subtraction, multiplication and division. Assume that $\otimes b_1 = [\underline{b}_1; \bar{b}_1]$ and $\otimes b_2 = [\underline{b}_2; \bar{b}_2]$ are grey numbers and \underline{b}_1 and \bar{b}_1 denote the lower and upper bounds of $\otimes b_1$. The basic mathematical operations of these grey numbers can be explained as follows [25].

$$\otimes b_1 + \otimes b_2 = [\underline{b}_1 + \underline{b}_2; \bar{b}_1 + \bar{b}_2] \quad (7)$$

$$\otimes b_1 - \otimes b_2 = [\underline{b}_1 - \underline{b}_2; \bar{b}_1 - \bar{b}_2] \quad (8)$$

$$\otimes b_1 \times \otimes b_2 = \left[\min(\underline{b}_1 \underline{b}_2, \underline{b}_1 \bar{b}_2, \bar{b}_1 \underline{b}_2, \bar{b}_1 \bar{b}_2); \max(\underline{b}_1 \underline{b}_2, \underline{b}_1 \bar{b}_2, \bar{b}_1 \underline{b}_2, \bar{b}_1 \bar{b}_2) \right] \quad (9)$$

$$\otimes b_1 \div \otimes b_2 = [\underline{b}_1; \bar{b}_1] \times \left[\frac{1}{\bar{b}_2}; \frac{1}{\underline{b}_2} \right] \quad (10)$$

Grey AHP

The AHP method is often used in the literature for solving complex MCDM problems. In this study, Grey AHP is utilised to compute the weights of criteria in a vague environment. Grey AHP is summarised in the following three steps:

Table 1. Linguistic expressions and grey numbers.

Linguistic expressions	Grey numbers
Extremely important	[7;9]
Very important	[5;7]
Important	[3;5]
Moderately important	[1;3]
Equally important	[1;1]

Step 1.1: First, decision makers (managers) compare criteria by giving a linguistic expression in a pair-wise comparison. Then these expressions are converted into grey numbers using **Table 1**. The grey numbers given by decision makers are integrated into **Equation (11)**. After this process, a grey comparison matrix ($\otimes C$) is structured.

$$\otimes c_{ij} = \left(\prod_{k=1}^K c_{ij}^k \right)^{1/K} \quad (11)$$

$$\otimes C = (\otimes c_{ij})_{n \times n} \quad i, j = 1, \dots, n \quad i \neq j \quad (12)$$

Each member of the grey comparison matrix ($\otimes C$) shown in **Equation (12)** is as follows:

$$\otimes c_{ij} = [\underline{c}_{ij}; \bar{c}_{ij}] \quad \text{and}$$

$$\otimes c_{ij}^{-1} = \left(\frac{1}{\underline{c}_{ij}}; \frac{1}{\bar{c}_{ij}} \right) \quad i, j = 1, \dots, n \quad (13)$$

$$\otimes c_{ii} = (1;1) \quad (14)$$

Once the grey comparison matrix ($\otimes C$) has been structured, it should be checked whether this matrix is consistent. To do this, each element of the grey comparison matrix is converted into crisp numbers by the following process (**Equation (15)**).

$$c_{ij} = \frac{(\underline{c}_{ij} + \bar{c}_{ij})}{2} \quad i, j = 1, \dots, n \quad (15)$$

The consistency index (*CI*) and consistency ratio (*CR*) are then calculated using **Equations (16)** and **(17)**, respectively [26].

$$CI = \frac{(\lambda_{\max} - n)}{(n-1)} \quad (16)$$

$$CR = (CI / RI(n)) \quad (17)$$

If the consistency ratio (*CR*) of the matrix is less than 0.1, proceed with step 1.2. Otherwise, the data are taken from the decision makers again and the same procedures repeated.

Step 1.2: Each row of the grey comparison matrix is summed using **Equation (18)**.

Table 2. Linguistic scores and grey numbers.

Linguistic scores	Grey numbers
Very high	[9;10]
High	[7;9]
Medium	[5;7]
Low	[3;5]
Very low	[1;3]

$$\otimes R_i = \sum_{j=1}^n [c_{ij}; \bar{c}_{ij}] \quad i, j = 1, \dots, n \quad (18)$$

Step 1.3: After calculation of the row sums ($\otimes R_i$), the lower and upper bounds of grey weights ($\otimes w_i$ (i th criterion weight)) are calculated using *Equations (20)* and *(21)*.

$$\otimes R_i = [R_i; \bar{R}_i] \quad i, j = 1, \dots, n \quad (19)$$

$$\otimes w_i = \left[\frac{2 \times R_i}{\sum_{i=1}^n R_i + \sum_{i=1}^n \bar{R}_i} \right] \quad i, j = 1, \dots, n \quad (20)$$

$$\otimes w_i = \left[\frac{2 \times \bar{R}_i}{\sum_{i=1}^n R_i + \sum_{i=1}^n \bar{R}_i} \right] \quad i, j = 1, \dots, n \quad (21)$$

$$\otimes w_i = [w_i; \bar{w}_i] \quad i, j = 1, \dots, n \quad (22)$$

Once the criteria weights are obtained, these values are transferred to ROV-G.

Table 3. Grey comparison matrix.

Criteria	C	EC	IC	MS
C	[1;1]	[5.593;7.612]	[5.593;7.612]	[4.217;6.257]
EC	[0.131;0.179]	[1;1]	[1;3]	[0.237;0.481]
IC	[0.131;0.179]	[0.333;1]	[1;1]	[0.160;0.237]
MS	[0.160;0.237]	[2.080;4.217]	[4.217;6.257]	[1;1]
P	[0.481;1]	[4.217;6.257]	[3.557;5.593]	[2.080;4.217]
S	[0.179;0.281]	[0.333;1]	[0.693;1]	[0.481;1]
W	[0.179;0.281]	[3.557;5.593]	[3;5]	[1;2.080]
ES	[0.121;0.160]	[0.333;1]	[0.333;1]	[0.333;1]
Criteria	P	S	W	ES
C	[1;2.080]	[3.557;5.593]	[3.557;5.593]	[6.257;8.277]
EC	[0.160;0.237]	[1;3]	[0.179;0.281]	[1;3]
IC	[0.179;0.281]	[1;1.442]	[0.200;0.333]	[1;3]
MS	[0.237;0.481]	[1;2.080]	[0.481;1]	[1;3]
P	[1;1]	[3;5]	[1.442;3.557]	[3.557;5.593]
S	[0.200;0.333]	[1;1]	[0.179;0.281]	[1;2.080]
W	[0.281;0.693]	[3.557;5.593]	[1;1]	[2.080;4.217]
ES	[0.179;0.281]	[0.481;1]	[0.237;0.481]	[1;1]

Consistency Ratio = 0.092 < 0.10

ROV-G

In this study, ROV-G is developed to rank sewing machines with respect to their performance for a textile company. The steps of normalisation and conversion into a crisp number utilised are taken from Wu and Lee [27]. The steps of ROV-G are as follows:

Step 2.1: Decision makers assign linguistic scores with respect to the performances of the alternatives against each criterion. These linguistic scores are then transformed into grey numbers by means of *Table 2*. With the aid of *Equation (11)*, these grey scores are aggregated and a grey decision matrix ($\otimes Y$) formed. In *Equation (23)*, $\otimes y_{it}$ represents the performance of the t th alternative for the i th criterion.

$$\otimes Y = (\otimes y_{it})_{m \times n} \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (23)$$

Step 2.2: The grey values in the grey decision matrix are normalised using *Equations (25)* and *(26)* (for non-beneficial criteria) and *Equations (27)* and *(28)* (for beneficial criteria).

$$\otimes y_{it}^* = [y_{it}^*; \bar{y}_{it}^*] \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (24)$$

$$y_{it}^* = \min \left(\frac{(\max_i y_{it}^* - y_{it}^*)}{\Delta_{\min}^{\max}}; \frac{(\max_i \bar{y}_{it}^* - \bar{y}_{it}^*)}{\Delta_{\min}^{\max}} \right) \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (25)$$

$$\bar{y}_{it}^* = \max \left(\frac{(\max_i y_{it}^* - y_{it}^*)}{\Delta_{\min}^{\max}}; \frac{(\max_i \bar{y}_{it}^* - \bar{y}_{it}^*)}{\Delta_{\min}^{\max}} \right) \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (26)$$

$$y_{it}^* = \frac{(y_{it}^* - \min_i y_{it}^*)}{\Delta_{\min}^{\max}} \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (27)$$

$$\bar{y}_{it}^* = \frac{(\bar{y}_{it}^* - \min_i \bar{y}_{it}^*)}{\Delta_{\min}^{\max}} \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (28)$$

$$\Delta_{\min}^{\max} = \max_i \bar{y}_{it}^* - \min_i y_{it}^* \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (29)$$

In *Equation (24)*, $\otimes y_{it}^*$ is the normalised value of $\otimes y_{it}$ and is a member of the grey normalized matrix ($\otimes Y^*$).

Step 2.3: After the normalization process, the best ($\otimes u_t^+$) and worst grey utility values ($\otimes u_t^-$) can be calculated using *Equations (30)* and *(31)*, respectively.

$$\otimes u_t^+ = \sum_{i=1}^n \otimes w_i \times \otimes y_{ij}^* \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (30)$$

$$\otimes u_t^- = \sum_{i=o+1}^n \otimes w_i \times \otimes y_{ij}^* \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (31)$$

Step 2.4: The final grey score ($\otimes u_t$) for each alternative can be obtained as follows:

$$\otimes u_t = \frac{\otimes u_t^+ + \otimes u_t^-}{2} \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (32)$$

Step 2.5: The final grey score ($\otimes u_t$) can be converted into a final crisp score (u_t) using *Equations (33)* and *(34)*.

$$V_t = \frac{(u_t(1 - \bar{u}_t) + (\bar{u}_t \times \bar{u}_t))}{(1 - \bar{u}_t + \bar{u}_t)} \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (33)$$

$$u_t = \min u_t + V_t \Delta_{\min}^{\max} \quad i = 1, \dots, n \quad t = 1, \dots, m \quad (34)$$

$$\Delta_{\min}^{\max} = \max(\bar{u}_t) - \min(u_t) \quad (35)$$

Table 4. Grey weights.

Criteria	$\otimes w_i$
C	[0.255;0.365]
EC	[0.039;0.093]
IC	[0.033;0.062]
MS	[0.084;0.151]
P	[0.160;0.267]
S	[0.034;0.058]
W	[0.121;0.203]
ES	[0.025;0.049]

Application

The model proposed was applied to select the best sewing machine for an apparel textile company located in Turkey. This company has over a thousand workers and has more than twenty-five years of experience in the apparel sector. The criteria to be taken into account in the method were determined by a council consisting of three managers, including the factory manager, purchasing manager, and operation’s manager. The data used in the model proposed were taken from these three managers of the company via questionnaires. The criteria determined by the council of managers are stated below:

- Cost (C)
- Energy Consumption (EC)
- Image of Company (IC)
- Maintenance and Service (MS)
- Productivity (P)
- Safety (S)
- Warranty Terms and Conditions (W)
- Ergonomic Suitability (ES)

The managers set the criteria as beneficial with the exception of the two non-beneficial criteria (Cost and Energy Consumption). The council of managers set 7 sewing machine brands as alternatives to evaluate their performance and to select the best one among them. Data (related to criteria comparison) obtained from the three managers are aggregated using **Equation (11)** to structure a grey comparison matrix ($\otimes C$), illustrated in **Table 3** ($\otimes C$).

The row sums ($\otimes R_i$) of the grey comparison matrix are calculated using equation 18. After calculation of the row sums, grey weights ($\otimes w_i$) are computed using **Equations (20)** and **(21)**. **Table 4** indicates the grey weights ($\otimes w_i$).

After obtaining the grey weights, data (related to the performance of alternatives) collected from the three managers are combined using **Equation (11)** to

Table 5. Grey decision matrix.

Criteria Alternatives	C	EC	IC	MS
Alternative 1	[3;5]	[3;5]	[5.593;7.612]	[5.593;7.612]
Alternative 2	[3.557;5.593]	[1.442;3.557]	[5.593;7.612]	[4.217;6.257]
Alternative 3	[4.217;6.257]	[1;3]	[6.257;8.277]	[4.217;6.257]
Alternative 4	[2.080;4.217]	[1.442;3.557]	[5;7]	[5.593;7.612]
Alternative 5	[4.217;6.257]	[2.080;4.217]	[3.557;5.593]	[5.593;7.612]
Alternative 6	[3;5]	[1.442;3.557]	[4.217;6.257]	[5;7]
Alternative 7	[3.557;5.593]	[1;3]	[5.593;7.612]	[5.593;7.612]
Criteria Alternatives	P	S	W	ES
Alternative 1	[4.217;6.257]	[5.593;7.612]	[4.217;6.257]	[4.217;6.257]
Alternative 2	[5;7]	[6.257;8.277]	[1.442;3.557]	[4.217;6.257]
Alternative 3	[5.593;7.612]	[5.593;7.612]	[2.080;4.217]	[2.080;4.217]
Alternative 4	[6.257;8.277]	[5.593;7.612]	[3.557;5.593]	[5;7]
Alternative 5	[6.257;8.277]	[4.217;6.257]	[5;7]	[5.593;7.612]
Alternative 6	[6.257;8.277]	[5;7]	[4.217;6.257]	[4.217;6.257]
Alternative 7	[5.593;7.612]	[6.257;8.277]	[4.217;6.257]	[3.557;5.593]

Table 6. Grey normalised matrix.

Criteria Alternatives	C	EC	IC	MS
Alternative 1	[0.291;0.301]	[0;0]	[0.431;0.859]	[0.405;1]
Alternative 2	[0.158;0.159]	[0.361;0.390]	[0.431;0.859]	[0;0.601]
Alternative 3	[0;0]	[0.500;0.500]	[0.572;1]	[0;0.601]
Alternative 4	[0.488;0.512]	[0.361;0.390]	[0.306;0.729]	[0.405;1]
Alternative 5	[0;0]	[0.196;0.230]	[0;0.431]	[0.405;1]
Alternative 6	[0.291;0.301]	[0.361;0.390]	[0.140;0.572]	[0.231;0.820]
Alternative 7	[0.158;0.159]	[0.500;0.500]	[0.431;0.859]	[0.405;1]
Criteria Alternatives	P	S	W	ES
Alternative 1	[0;0.502]	[0.339;0.836]	[0.499;0.866]	[0.386;0.755]
Alternative 2	[0.193;0.685]	[0.502;1]	[0;0.381]	[0.386;0.755]
Alternative 3	[0.339;0.836]	[0.339;0.836]	[0.115;0.499]	[0;0.386]
Alternative 4	[0.502;1]	[0.339;0.836]	[0.381;0.747]	[0.528;0.889]
Alternative 5	[0.502;1]	[0;0.502]	[0.640;1]	[0.635;1]
Alternative 6	[0.502;1]	[0.193;0.685]	[0.499;0.866]	[0.386;0.755]
Alternative 7	[0.339;0.836]	[0.502;1]	[0.499;0.866]	[0.267;0.635]

Table 7. Results.

Results Alternatives	$\otimes u_i^-$	$\otimes u_i^+$	$\otimes u_i$	u_i	Ranking
Alternative 1	[0.074;0.110]	[0.130;0.599]	[0.102;0.355]	0.130	5
Alternative 2	[0.054;0.094]	[0.072;0.499]	[0.063;0.297]	0.108	6
Alternative 3	[0.020;0.047]	[0.099;0.544]	[0.060;0.296]	0.107	7
Alternative 4	[0.138;0.223]	[0.195;0.707]	[0.167;0.465]	0.171	1
Alternative 5	[0.008;0.021]	[0.207;0.726]	[0.108;0.374]	0.136	4
Alternative 6	[0.088;0.146]	[0.181;0.679]	[0.135;0.413]	0.151	2
Alternative 7	[0.060;0.105]	[0.186;0.692]	[0.123;0.399]	0.145	3

construct a grey decision matrix ($\otimes Y$), shown in **Table 5** ($\otimes Y$).

In the normalisation procedure, **Equations (25)** and **(26)** are used to normalise grey values under non-beneficial criteria, and **Equations (27)** and **(28)** are used to normalise grey values under beneficial

criteria. **Table 6** presents the grey normalised matrix ($\otimes Y^*$).

Grey values in the grey normalised matrix ($\otimes Y^*$) are multiplied by grey weights ($\otimes w_i$) to calculate the best ($\otimes u_i^+$) and worst grey utility values ($\otimes u_i^-$). **Table 7** presents the best grey utility values

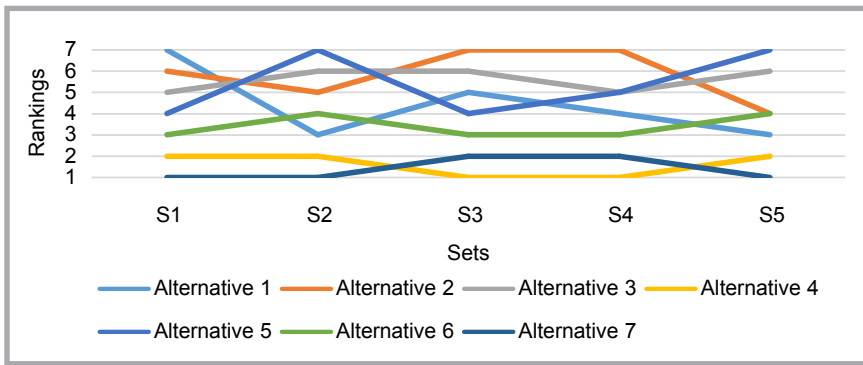


Figure 1. Results of sensitivity analysis.

Table 8. Comparison of methods.

Methods Alternatives	ROV-G	COPRAS-G	ARAS-G
Alternative 1	5	5	5
Alternative 2	6	7	7
Alternative 3	7	6	6
Alternative 4	1	1	1
Alternative 5	4	4	4
Alternative 6	2	2	3
Alternative 7	3	3	2

Table 9. Sensitivity analysis.

Criteria	Set 1	Set 2	Set 3	Set 4	Set 5
C	[0.030;0.050]	[0.150;0.160]	[0.160;0.170]	[0.100;0.120]	[0.050;0.070]
EC	[0.200;0.300]	[0.100;0.200]	[0.140;0.160]	[0.040;0.080]	[0.100;0.120]
IC	[0.030;0.040]	[0.170;0.190]	[0.100;0.150]	[0.200;0.250]	[0.100;0.200]
MS	[0.080;0.100]	[0.070;0.100]	[0.090;0.150]	[0.070;0.100]	[0.150;0.200]
P	[0.150;0.270]	[0.030;0.070]	[0.170;0.240]	[0.140;0.230]	[0.060;0.090]
S	[0.120;0.150]	[0.120;0.150]	[0.030;0.060]	[0.100;0.120]	[0.250;0.270]
W	[0.140;0.220]	[0.160;0.180]	[0.120;0.180]	[0.120;0.200]	[0.100;0.130]
ES	[0.040;0.080]	[0.050;0.100]	[0.030;0.050]	[0.050;0.080]	[0.050;0.060]

($\otimes u_i^+$), the worst grey utility values ($\otimes u_i^-$), the final grey score ($\otimes u_i$), and the final crisp score (u_i).

The order of the alternatives according to Table 7 is as follows: Alternative 4 > Alternative 6 > Alternative 7 > Alternative 5 > Alternative 1 > Alternative 2 > Alternative 3. To test the accuracy of the results, ROV-G results are compared to those of the Grey COPRAS [28] and Grey ARAS [29] methods. The same weights of criteria (obtained in Grey AHP) are used in Grey COPRAS and Grey ARAS. Table 8 shows a comparison of the results.

The results of these three methods are analysed using the Spearman Correlation. The correlation coefficients between the results are as follows; 0.964 (ROV-G and COPRAS-G) and 0.929 (ROV-G and ARAS-G). As can be seen from the correlation coefficients, the ROV-G method

achieved similar results as compared with other grey MCDM methods.

Sensitivity analysis

A sensitivity analysis is conducted to monitor the change in the rankings of alternatives with respect to that in the criteria's grey weights. Five sets of grey weights of the criteria are designated for the sensitivity analysis. Table 9 presents these sets.

The sensitivity analysis is performed using these sets. The results of the sensitivity analysis are demonstrated in Figure 1.

As can be seen, Alternative 7 is designated as the best one in Set 1, Set 2 and Set 5, while Alternative 4 is determined as the best one in Set 3 and Set 4. Additionally, changes in the rankings of other alternatives are observed. Conse-

quently, changes in criteria weights lead to variations in the rankings of alternatives. Therefore, ROV-G is revealed to be sensitive to change in the weights of the criteria.

Conclusions

The aim of this study is to propose a new grey integrated model including Grey AHP and ROV-G to identify the most appropriate sewing machine for a textile company. According to the results of the grey integrated model, the ranking of alternatives is as follows; Alternative 4 > Alternative 6 > Alternative 7 > Alternative 5 > Alternative 1 > Alternative 2 > Alternative 3. Therefore, Alternative 4, with the best performance, is selected. The COPRAS-G and ARAS-G methods were applied to the same data to test whether the model proposed had achieved the correct results or not. The results of the three methods were analysed by the Spearman correlation method. It is seen that the correlation coefficients are high and that the results are very similar to each other. Therefore, the ROV-G method was proved to achieve successful results. Additionally, the results of the ROV-G method were shown to the company's factory manager, who evaluated the results and concluded that they were correct and said that the company would purchase 20 of the sewing machine coded Alternative 4 for now. Thus, it was confirmed that the ROV-G method achieved the correct results both by comparing with other grey MCDM methods and by consulting the factory manager. It can be said that the benefits of the ROV-G method are that its computation steps are easy and the correct result is achieved in a short time. Additionally, the ROV-G method was proven to be sensitive to criteria weights in the sensitivity analysis section. The study contributes to the literature in three ways: The first is the development a new grey method called ROV-G. The second is that it is the first time in the literature that the Grey AHP and ROV-G methods have been used together to solve the machine selection problem. In the literature, there are few studies related to the sewing machine selection problem, and hence the third contribution of this study is the filling of this research gap. Future studies may use ROV-G in solving other MCDM problems, such as location, supplier and warehouse selection.

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