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Authors: Batuhan ÖZAKIN Kürşat GÜLTEKİN

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MATERIAL SELECTION FOR METAL ADDITIVE MANUFACTURING USING MULTI-CRITERIA DECISION MAKING METHODS

Batuhan ÖZAKIN[1*] Kürşat GÜLTEKİN[2]

[1]Samsun University, Faculty of Engineering and Natural Sciences, Department of Mechanical Engineering, Samsun, Türkiye.
[2]Ondokuz Mayıs University, Faculty of Engineering, Department of Mechanical Engineering, Samsun, Türkiye.

[*]Corresponding Author: batuhan.ozakin@samsun.edu.tr

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ABSTRACT: Additive manufacturing has attracted attention as a new generation manufacturing method that has found widespread use in many industries in recent years due to its many advantages over traditional manufacturing methods. The materials used in metal additive manufacturing technology have a wide range. Therefore, making the ideal choice among these preferable materials is very important. Multi-criteria decision making (MCDM) techniques are reliable and effective methods in material selection processes and are effectively used in material selection processes. In this study, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and Additive Ratio Assessment (ARAS) methods were applied to the selection process among different criteria and materials for metal additive manufacturing. It was observed that AlSi12Cu2Fe material ranked first in the TOPSIS method, while H13 material ranked first in the ARAS method. The second place was taken by H13 material in the TOPSIS method and AlSi12Cu2Fe material in the ARAS method. A strong relationship exists between TOPSIS and ARAS methods with a Pearson correlation coefficient of 0.977. It has been concluded that it will be more effective to decide according to the nature of the technological application in the use of the materials that rank first two in TOPSIS and ARAS methods in additive manufacturing.

Keywords: TOPSIS, ARAS, Additive Manufacturing, Correlation, MCDM.

1. INTRODUCTION

Metal additive manufacturing (MAM) is a manufacturing system that combines metal materials layer by layer from a digital model of the product into physical objects. It offers a desirable and widespread manufacturing option compared to traditional manufacturing methods due to its many advantages, such as manufacturing complex shapes and eliminating waste material and tooling costs. Additive manufacturing (AM) includes various technologies such as metal laser sintering, selective laser melting, and direct metal deposition, which differ in process, material, and power source. Recently, it has been used extensively in many industries, especially aerospace and automotive [1-4].

Choosing among thousands of materials in metal additive manufacturing is challenging due to the complexity of benefits, performance, and limitations. In material selection, it is necessary to optimise component quality, properties, manufacturability, and cost. For all these reasons, material selection is one of the most critical issues in metal additive manufacturing [5-7]. Many approaches have been developed in the literature for material selection in additive manufacturing. One of the most effective of these approaches is multi-criteria decision making methods. Issues such as optimization of materials and manufacturing processes in additive manufacturing with multi-criteria decision making methods have been evaluated [8-10]. These studies are given in order. Mahapatra and Panda [11] preferred GRA (Grey Relational Analysis) and fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) for the selection of additive manufacturing processes. Kek et al. [12] used ANP (analytic network process)-TOPSIS method to select an ideal additive manufacturing process. Alghamdy et al. [13] stated that the AHP (analytic hierarchy process) method is an appropriate process in the selection process among many materials used in additive manufacturing and developed a heuristic and analytical algorithm for a systematic material selection. Palanisamy et al. [14] used BWM (best-worst method) to select the most suitable materials for additive manufacturing machines. Raigar et al. [15] used the PIV (Proximity Indexed Value) method to select additive manufacturing processes. They showed that material spraying is effective in manufacturing quality and precise parts among additive manufacturing processes. Malaga et al. [16] used IEM (information entropy method) and CODAS (combinatorial distance-based assessment) methods for material selection for metal additive manufacturing. According to the analysis results, an aluminum-based alloy material is the most ideal material. Chandra et al. [17], using SWARA (stepwise weight assessment ratio analysis) - COPRAS (complex proportional assessment) hybrid multi-criteria decision making approach, found that the fused diffusion modeling (FDM) method was the best among four different additive manufacturing processes. Qin et al. [18] proposed a three-stage decision-making approach for material selection in metal additive manufacturing. In the first stage, decision matrix construction and normalization, in the second stage, the summary loss function was calculated according to gray relational analysis and three-way decision theory. In the third and final stage, they selected the best material according to the results obtained. Srinivas and Vimal [19] proposed an integrated AHP-PROMETHEE multi-criteria decision making (MCDM) approach to select the best process from five metal additive manufacturing processes: selective laser melting, direct metal laser sintering, laser engineered net shaping, electron beam melting, and wire arc additive manufacturing process. Junaid et al. [20] developed a hybrid AHP-TOPSIS multi-criteria decision-making (MCDM) approach and applied it to the material selection process for additive manufacturing in aerospace applications.

The studies in the literature reveal that multi-criteria decision making methods are used to select materials and manufacturing processes in additive manufacturing processes effectively. However, it is seen that the use of multi-criteria decision making methods for selecting materials used in metal additive manufacturing is quite limited. In the literature, TOPSIS and Additive Ratio Assessment (ARAS) methods were used to select the materials used in metal additive manufacturing. The correlation relations between these methods were evaluated by considering the CODAS method used in the reference source. The methods used in the study confirmed the preferences obtained in the literature. Also, multi-criteria decision making methods have become more efficient, systematic, and objective. Thus, it has provided innovative solutions by making it possible to make more strategic, effective, and dynamic decisions in the industry.

2. MATERIAL AND METHODS

2.1. Materials

In material selection for metal additive manufacturing, the materials, criteria and weight coefficients used in the study by Malaga et al. [16] were taken as reference. Material selection processes were carried out according to 8 alternative materials and 9 different criteria used in the study. The properties of the materials and criteria are given in Table 1. Table 1 also contains the decision matrix of the additive manufacturing material selection process.

Table 1. Specifications of materials and criteria [16].

Material	**D (g/cm^3)**	**MP (˚C)**	**SH (J/kg.K)**	**TS (MPa)**	**EM (GPa)**	**TC (W/m.K)**	**C (cost/kg)**	**H (Brinell)**	**ER (mΩ-m)**
H13	7.8	1427	460	1380	215	28.6	190	207	0.52
316L	8	1400	500	170	193	16.3	380	217	0.74
Ti6Al4V	4.42	1649	560	910	114	7.2	1990	334	1.78
AlSi12Cu2Fe	2.67	585	963	140	74.5	180	650	100	0.075
AlSi10Mg	2.58	600	900	190	70	150	280	75	0.05943
Inconel 718	8.192	1426	435	550	204.9	11.4	3000	363	1.182
Hastelloy X	822	1316	784	385	205	9.1	4000	230	1.18
CuSn10	8.8	999	380	180	130	50	600	70	0.16

Among these criteria, density (D), specific heat (SH), tensile strength (TS), elasticity modulus (EM), thermal conductivity (TC), hardness (H), and electrical resistivity (ER) are the maximum (useful) criteria. Melting point (MP) and cost (C) are minimum (not useful) criteria. The hierarchical model applied to the selection process for metal additive manufacturing with reference to nine criteria and eight materials is presented in Figure 1.

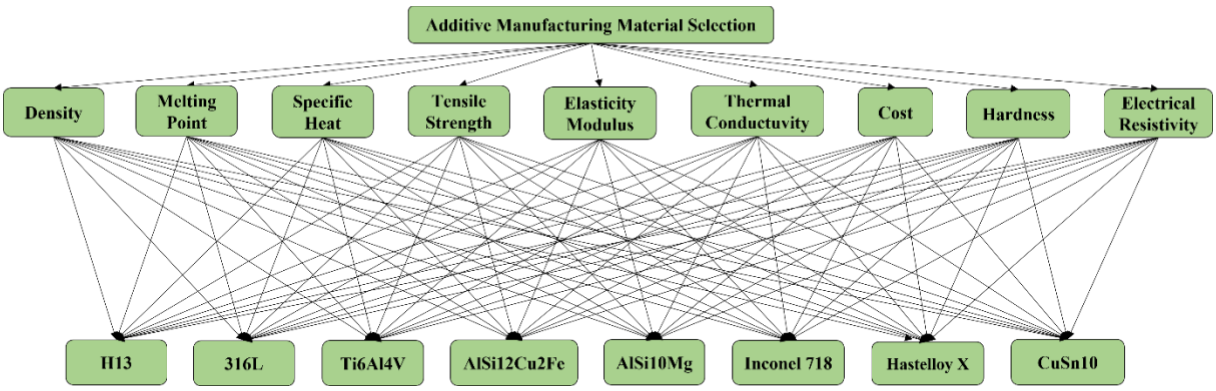

Figure 1. A hierarchical model was applied to the metal additive manufacturing material selection process.

The process steps applied to the material selection process for metal additive manufacturing are given in Figure 2. The alternatives and criteria from the reference study were followed by TOPSIS and ARAS methods to determine the best material. The correlation relationships between the TOPSIS and ARAS methods and the CODAS method used in the reference study were determined, and the interconnections between the methods were evaluated.

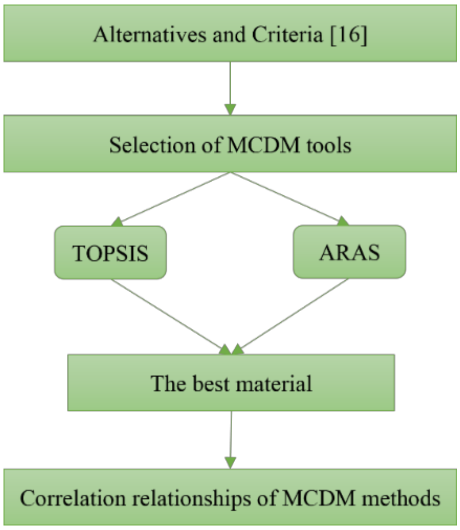

Figure 2. Process steps applied to the material selection process for metal additive manufacturing.

2.2. Methods

2.2.1. TOPSIS Method

TOPSIS method was developed by Hwang and Yoon [21] and is the most frequently used multi-criteria decision making method in the literature. The procedure steps are given below [22].

First, the decision matrix (X) is obtained from the material and criteria properties given in Table 1 with the help of Equation (1). After the decision matrix is created, the decision matrix is normalized with the help of Equation (2).

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix} \tag{1}$$

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}}, i = 1,2, \ldots, m, j = 1,2, \ldots, n \tag{2}$$

After the decision matrix is normalized, the next step is to create a weighted normalized decision matrix by multiplying the weight coefficients of the criteria (W_j). The weighted standard decision matrix (V) is created by performing the operations given in Equation (3).

$$V_{ij} = x_{ij}^{*}.W_j \; ; \; i = 1,2, \ldots, m, j = 1,2, \ldots, n \tag{3}$$

Positive and negative solution values are obtained after obtaining the weighted standard decision matrix. The positive ideal solution set is defined as $V^{+} = \{v_1^{+}, v_2^{+}, \ldots \ldots, v_n^{+}\}$ and the negative ideal solution set as $V^{-} = \{v_1^{-}, v_2^{-}, \ldots \ldots, v_n^{-}\}$. Then, using Equation (4), the distance to the positive ideal solution values (S_i^{+}) is calculated and using Equation (5), the distance to the negative ideal solution values (S_i^{-}) is calculated.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{4}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{5}$$

In the last stage, the closeness coefficients (C_i) are calculated for each decision option using Equation (6). The closeness coefficients in the range [0, 1] are ranked, and the highest value is determined as the best material.

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{6}$$

2.2.2. ARAS Method

ARAS method is a method developed by Zavadskas and Turskis [23]. ARAS method is one of the reliable multi-criteria decision making methods used today due to some advantages such as ease of operation. The mathematical steps of the method are given below [24].

In the first stage of the process, the decision matrix is created as given in Equation (1) by considering the criteria and material properties in Table 1. The normalization operations of the criteria that are not useful features are carried out with the help of Equation (7) and Equation (8). The normalization of the useful criteria is achieved by applying Equation (8) in a single step.

$$x_{ij}^* = \frac{1}{x_{ij}} \tag{7}$$

$$x_{ij}^* = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}^*} \tag{8}$$

After the decision matrix is normalized, the weighted normalized decision matrix is obtained. The weighted standard decision matrix (V) is created by performing the operations given in Equation (3). After obtaining the weighted decision matrix, the values of the optimality function, which is one of the essential steps of the ARAS method, are calculated using Equation (9). The calculated values (D_i) are the optimality function values of alternative i.

$$D_i = \sum_{j=1}^{n} x_{ij}^*;\ i = 1,2, \ldots, m \tag{9}$$

The D_i values of the alternatives are rated to the optimal function value D_0 by applying Equation (10). The values obtained are determined as benefit values P_i, which are in the range [0, 1]. The calculated benefit values are ranked, and the highest benefit value is determined as the best material.

$$P_i = \frac{D_i}{D_0} \; ; \; i = 1,2, \dots, m \tag{10}$$

3. RESULTS AND DISCUSSIONS

3.1. TOPSIS Method

The first method used in material selection for metal additive manufacturing is the TOPSIS method. In Table 1, the normalized decision matrix of materials and alternatives is written in the form given in Equation (1) and the normalized decision matrix values are obtained by applying Equation (2). The decision matrix values are shown in Table 2. The next step after this stage is to determine the values of the weighted normalized decision matrix.

Table 2. Normalized decision matrix.

Material	D	MP	SH	TS	EM	TC	C	H	ER
1	0.405	0.417	0.247	0.760	0.472	0.118	0.035	0.325	0.199
2	0.416	0.409	0.269	0.094	0.423	0.067	0.069	0.340	0.284
3	0230	0.482	0.301	0.501	0.250	0.030	0.363	0.524	0.682
4	0.139	0171	0.518	0.077	0.163	0.743	0.119	0.157	0.029
5	0.134	0.175	0.484	0.105	0.154	0.619	0.051	0.118	0.023
6	0.426	0.364	0.234	0.303	0.449	0.047	0.548	0.569	0.453
7	0.427	0.385	0.421	0.212	0.450	0.038	0.730	0.361	0.452
8	0.457	0.292	0.204	0.099	0.285	0.206	0.110	0.110	0.061

The normalized decision matrix values were then multiplied by the weight coefficients used in the reference study by applying Equation (3). The weight coefficients and weighted normalized decision matrix values are given in Table 3.

Table 3. Weighted normalized decision matrix.

Material	D	MP	SH	TS	EM	TC	C	H	ER
W_j [16]	0.081	0.085	0.104	0.172	0.084	0.199	0.050	0.104	0.121
Material	**D**	**MP**	**SH**	**TS**	**EM**	**TC**	**C**	**H**	**ER**
1	0.033	0.036	0.026	0.131	0.040	0.023	0.002	0.034	0.024
2	0.034	0.035	0.028	0.016	0.036	0.013	0.003	0.035	0.034
3	0.019	0.041	0.031	0.086	0.021	0.006	0.018	0.054	0.082
4	0.011	0.015	0.054	0.013	0.014	0.147	0.006	0.016	0.003
5	0.011	0.015	0,050	0.018	0.013	0.123	0.003	0.012	0.003
6	0.035	0.031	0,024	0.052	0.038	0.009	0.027	0.059	0.055
7	0.035	0.033	0,044	0.037	0.038	0.007	0.037	0.037	0.054
8	0.037	0.025	0,021	0.017	0.024	0.041	0.005	0.011	0.007

The distance (S_i^+) values to the positive ideal solution values using Equation (4), the distance (S_i^-) values to the negative ideal solution values using Equation (5), and the closeness coefficients (C_i) determined using Equation (6) are given in Table 4. According to the closeness coefficients, the material selection ranking for metal additive manufacturing is also shown in Table 4.

Table 4. Positive, negative ideal solution values, closeness coefficients and material selection rankings.

Material	S_i^+	S_i^-	C_i	Rank
1	0.146	0.129	0.469	2
2	0.189	0.056	0.228	7
3	0.154	0.121	0.441	3
4	0.158	0.145	0.480	1
5	0.158	0.121	0.432	4
6	0.165	0.093	0.360	5
7	0.173	0.085	0.328	6
8	0.186	0.047	0.201	8

3.2. ARAS Method

The second method used in material selection for metal additive manufacturing is the TOPSIS method. In Table 1, the decision matrix of materials and alternatives is written in the form given in Equation (1) and normalized decision matrix values are obtained by applying Equation (7) and Equation (8).

Table 5. Normalized decision matrix.

Material	D	MP	SH	TS	EM	TC	C	H	ER
1	0.154	0.088	0.092	0.353	0.178	0.063	0.334	0.130	0.091
2	0.158	0.090	0.100	0.044	0.160	0.036	0.167	0.136	0.130
3	0.087	0.076	0.112	0.233	0.094	0.016	0.032	0.209	0.312
4	0.053	0.215	0.193	0.036	0.062	0.398	0.098	0.063	0.013
5	0.051	0.209	0.181	0.049	0.058	0.331	0.227	0.047	0.010
6	0.162	0.101	0.087	0.141	0.170	0.025	0.021	0.227	0.207
7	0.162	0.095	0.157	0.099	0.170	0.020	0.016	0.144	0.207
8	0.174	0.126	0.076	0.046	0.108	0.110	0.106	0.044	0.028

The obtained normalized decision matrix values were multiplied by the weight coefficients using Equation (3), and a weighted normalized decision matrix was obtained. The weighted normalized decision matrix is given in Table 6.

Table 6. Weighted normalized decision matrix.

Material	D	MP	SH	TS	EM	TC	C	H	ER
1	0.013	0.008	0.010	0.061	0.015	0.013	0.017	0.013	0.011
2	0.013	0.008	0.010	0.008	0.014	0.007	0.008	0.014	0.016
3	0.007	0.006	0.012	0.040	0.008	0.003	0.002	0.022	0.038
4	0.004	0.018	0.020	0.006	0.005	0.079	0.005	0.006	0.002
5	0.004	0.018	0.019	0.008	0.005	0.066	0.011	0.005	0.001
6	0.013	0.009	0.009	0.024	0.014	0.005	0.001	0.024	0.025
7	0.013	0.008	0.016	0.017	0.014	0.004	0.001	0.015	0.025
8	0.014	0.011	0.008	0.008	0.009	0.022	0.005	0.005	0.003

After constructing the weighted normalized decision matrix, Equation (9) and Equation (10) were used to determine the optimality function and benefit values, respectively. The optimality function (D_i) and benefit values (P_i) are given in Table 7. According to the benefit values, the material selection ranking for metal additive manufacturing is also given in Table 7.

Table 7. Optimality function (D_i), benefit values (P_i) and material selection rankings.

Material	D_i	P_i	Rank
1	0,159	1,000	1
2	0,097	0,610	7
3	0,138	0,863	3
4	0,146	0,917	2
5	0,137	0,862	4
6	0,124	0,779	5
7	0,114	0,714	6
8	0,085	0,534	8

3.3. Comparison of Methods

The findings of the TOPSIS and ARAS methods used in this study and the CODAS methods utilized in the reference study were compared with each other in material selection for metal additive manufacturing. The material selection rankings obtained from TOPSIS, ARAS and CODAS methods for additive manufacturing are given in Figure 3. It was determined that AlSi12Cu2Fe material ranked first in TOPSIS and CODAS methods, while H13 material ranked first in the ARAS method. While H13 material ranked second in TOPSIS and CODAS methods, AlSi12Cu2Fe material ranked second in the ARAS method. In all three methods, CuSn10 material took the last place in the material selection ranking for additive manufacturing. In fact, it indicates that the materials with the best top two rankings in all three methods are AlSi12Cu2Fe and H13 materials, which are in line with the methods used in the study. When the rankings obtained in this study are evaluated with the reference article, it is seen that the materials that take the first two and last places in the CODAS and TOPSIS methods are the same. It is also seen that the ranking in the ARAS method is quite close to the rankings obtained in the CODAS and TOPSIS methods. When the TOPSIS method is considered as the most frequently preferred multi-criteria decision-making method in the literature, it can be stated that the rankings obtained in the reference study are confirmed and the findings become objectively more efficient. Moreover, in this direction, evaluating the correlation relationships between the methods is very effective in determining the relationships between the methods.

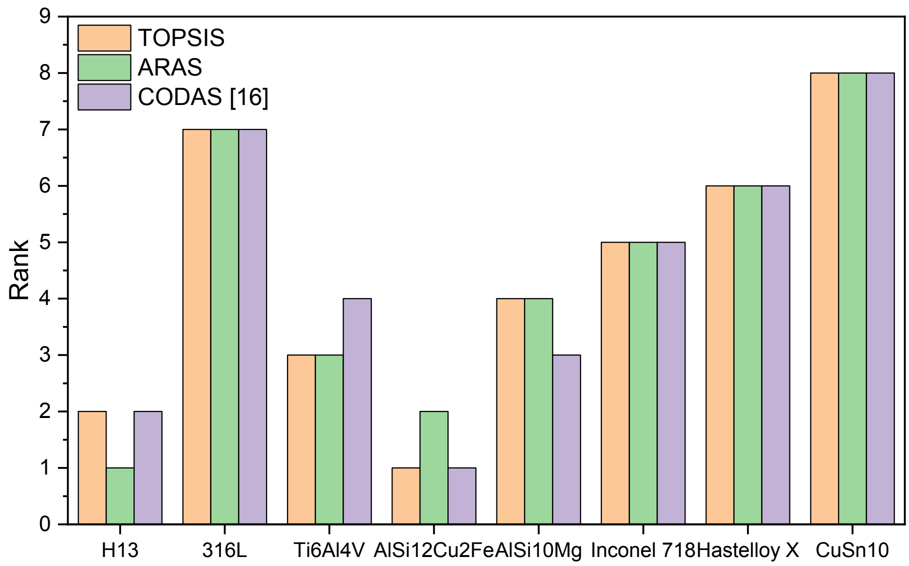

Figure 3. Material selection rankings were obtained from TOPSIS, ARAS, and CODAS methods for additive manufacturing.

Correlation tests are used to compare the TOPSIS and ARAS methods used in this study and the CODAS methods used in the reference study to select materials for metal additive manufacturing. Correlation tests determine the strength of the relationship between the methods used. Pearson correlation test is one of these correlation tests, and a correlation above 0.8 indicates a strong relationship between the methods [25, 26].

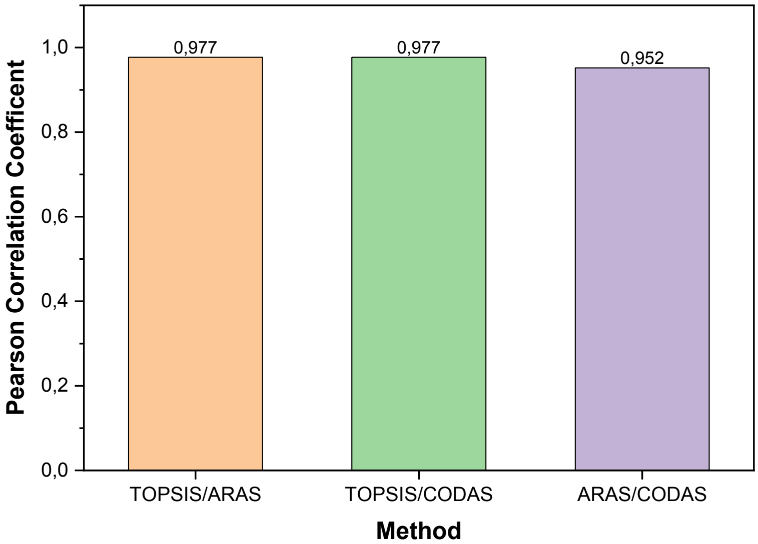

Figure 4. Correlation relationships between methods used in material selection for metal additive manufacturing.

Figure 4 shows the correlation relationships between the methods used in material selection for metal additive manufacturing. It is seen that the correlation between TOPSIS and ARAS methods used in the study is very strong, with a Pearson correlation coefficient of 0.977. It is also noteworthy that the Pearson correlation coefficients between TOPSIS/CODAS and ARAS/CODAS methods are 0.977 and 0.952, respectively. It is seen that there are strong correlation relationships between these methods.

It was determined that the best material obtained from TOPSIS and CODAS methods for material selection for metal additive manufacturing was AlSi12Cu2Fe. The use of these Al-Si based alloys in metal additive manufacturing is expected to cause changes in the structure of the material and result in changes in its mechanical properties [27]. Due to these advantages of these Al-Si based alloys, it shows that they can be used safely in metal additive manufacturing. The best material obtained from the ARAS method in material selection for metal additive manufacturing was determined to be H13 tool steel. When the H13 tool steel material used for metal additive manufacturing is produced with the additive manufacturing technique, it has a unique microstructure compared to the materials manufactured by the traditional manufacturing technique [28]. In this way, it exhibits highly effective mechanical properties. Therefore, it is possible to say that it can be used safely with the appropriate manufacturing technology choice for metal additive manufacturing. The nature of the technological application will be more effective in the selection process between AlSi12Cu2Fe and H13 materials.

4. CONCLUSIONS

In this study, the material selection process used in the metal additive manufacturing method was carried out using TOPSIS and ARAS methods. The correlation relations between these methods were evaluated by considering the CODAS method used in the reference source. The results obtained in the study are presented below.

- While AlSi12Cu2Fe material ranked first in the TOPSIS method, H13 material ranked first in the ARAS method. The second place was taken by H13 material in the TOPSIS method and AlSi12Cu2Fe material in the ARAS method.
- It is determined that there is a strong relationship between the TOPSIS and ARAS methods used in the study with a Pearson correlation coefficient of 0.977. It was also found that there are very strong correlation relationships between the existing methods and the CODAS methods in the reference study.
- Since a unique structure is obtained using Al-Si based alloy material AlSi12Cu2Fe and H13 tool steel material in additive manufacturing, it is concluded that it would be more effective to decide according to the nature of the technological application.

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