TAGUCHI ADDITIVE RATIO ASSESSMENT (ARAS) METHOD IN MULTI-CRITERIA DECISION MAKING: A CASE STUDY FOR TREATED DRILL TOOLS PERFORMANCE

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Abstract: The multi-criteria Decision Making (MCDM) approach is used in many areas of engineering applications. Each of the multi-criteria Decision Making can be described by a set of criteria. Criteria can be qualitative and quantitative. They usually have different units of measurement and different directions of optimization. Normalization is used to obtain comparable standard values. This article introduces a new evaluation method for the Taguchi Additive Ratio ASsessment (ARAS). To illustrate the ARAS method described, a practical study was conducted on the AM60 using a 4mm HSS class cutting tool, and all this was carried out throughout the test under different cutting conditions. The case study aims to use a system to determine machining parameters to obtain minimum Geometric Dimension and tolerances, surface roughness (Ra) and tool wear to determine measures to improve the environment. Based on the analysis, the following criteria for evaluating the parameters of the drilling process parameter are recommended: as the response. Standard weights are determined by pair comparison methods based on expert estimates.

Keywords: MCDM, decision, alternative, ARAS, weights, cutting, ANOVA.

1. INTRODUCTION

Real-world decision-making issues are often too complex and unstructured to be considered by examining individual criteria or perspectives, which would lead to optimal decision-making. Technological advances and innovations in civil and mechanical engineering, management, and living conditions have had a huge impact on economic activity, employment, and growth rates. All issues related to property management decisions (Langston et al., 2008). Are increasingly complex and interplay. In many real-world decision-making issues, decision-makers have a set of multiple conflicting objectives. All new ideas and possible variants of decision-making must be compared according to many criteria (Turskis et al., 2009). The problem for decision-makers includes assessing a limited set of alternatives to find the best alternatives, ranking them from best to worst, dividing them into predefined homogenous classes, or describing how each of the alternatives can simultaneously meet the criteria for determining a set of alternatives based on a set of decision criteria. In the multi-criteria approach, the analyst tries to establish several criteria using several points of view. MCDM is one of the most widely used decision-making methods in science, business and government that, based on the assumptions of a complex world, can improve the quality of decision-making by making the decision-making process more clear, reasonable and efficient. In real life, decision-makers must first understand and describe the situation. This phase includes the identification and assessment of stakeholders, different options for feasible actions, a large number of different and important criteria for decision-making, the type and quality of information, etc. This seems to be the key point to define MCDM as a formal method. For (Zeleny, 1982), decision criteria are the rules, measures, and standards that guide decision making. For the first time in 1896, Pareto applied the classical multiple optimization methods and determined the priority and utility functions (Pareto, 1971). These methods are closely related to economic theory and involve the average of thousands of decisions. To meet the growing needs of human society and the environment, multivariate analysis methods have been developed. (Keeney and Raiffa, 1976) provide the representation theorem for determining utility functions of multi-valued profit margins under the preferential and utility independent hypotheses (Saaty, 1977) by using the multi-criteria model, the global importance of solving problems with conflicting objectives is demonstrated, and a decision-making model with incomplete information proposed. (Keeney, 1982) gives an overview of the basic features and concepts of decision analysis, formulation of the axioms, and the main stages. (Keeney and Winterfeldt, 2001) authors recommends following the principle of prudence in the decision-making process, precise decision-making, and evaluation of all possible alternatives, the objectives of the parties involved, the subsequent change in the decision-making results and values, in this minimizing the risk of decision-making. (Guitoni and Martel, 1998) note that there are a number of different approaches to the analysis of multiple criteria that can be suggested depending on the circumstances of the decision. In the MCDM approach, it is necessary first to clarify the definition of the problem and then to identify realistic alternatives. It is important to define actors involved in decision-making, select the assessment criteria, and evaluate each of the alternatives according to the set of criteria. Next, select the MCDM method to aggregate the performance of each alternative. Podvezko V. and Podviezko A first recognized the necessity of comparing the MCDM method and the importance of the problem of selection (Podvezko and Podviezko, 2010) who suggested the classification of the MCDM method. There are many comparative studies presented in scientific research work. Guitoni and Martel (Larichev, 2000) proposed a methodological approach to the selection of suitable MCDM methods for specific decision situations. The calculation of different examples reveals the fact that the results of the assessment depend on the choice of utility functions and their parameters (Hwang and Yoon, 1981). (Kelemenis et al., 2011) present a review of recent studies on personnel selection issues (from 1992 to 2009). For example, there are commonly used fuzzy number, OWA operator, AHP, AHP, network analysis, fuzzy TOPSIS, fuzzy multiple target planning, discriminant analysis, decision tree, neural network analysis, the sum of the law, simple additive weighted method, weighted over the past two decades is changing customer needs of the Times. There was a lively academic and political debate on the continuing gender process of the accounting profession, as summarized (Heidhues and Patel, 2011). There are two areas of Accounting: Financial Accounting and management accounting. When running a business, the external business accountant is the core of the intellectual capital of the company. (Seifert et al., 2010) applied the theory of organizational justice to the design of whistle blowing policies and procedures. The figures used in financial accounting are usually very conservative in nature. Management accounting provides customized, appropriate, and timely financial information for internal managers who are entrusted with the day-to-day operations of an organization. (Lambert and Pezet, 2011) analyzes the practice of establishing management accountants. (Tillmann and Goddard, 2008). Established a solid theory of Strategic Management. It is not enough to 'simple' Know accounting or management accounting techniques, but there is a need for broader know-how. The use of measures of individuality to predict work performance has a long and legendary history (Penney et al., 2010). However the methodological progress of meta-analysis techniques and the emergence of now widely accepted five large personality models-conscience, extroversion, cheerfulness, emotional stability and openness to experience a renewed interest in personality as a choice of academia in recent decades, interest in low-temperature effects has been particularly manifested in the tool steel heat treatment cycle. Some literature data indicate that the life of tools and other steel components may increase significantly at temperatures below zero (below 0°C). The results can be surprisingly good, depending on the application. After reports of a 92% to 817% increase in tool life, they are being processed in-196°C to be found (Paulin, 1993). The first user of this technique (Gulyaev, 1937) applies approximately 30min–1h over a temperature range of -80°C to -100°C, and the improvement in tool life is attributed to the conversion of residual austenite (softer) to martensite (harder) and the production of more generally, the addition of alloying elements reduces the Ms (start temperature of martensite transition) and Mf (final transition temperature). Conventional heat treatment is usually used only cooling conditions until room temperature, which may leave some residual austenite in the microstructure. This fact must be taken into account during the heat treatment of tool steel. For eutectoid Steels, the Mf temperature is about -50°C, so a certain percentage of retained austenite is present after quenching (Zamborsky, 1986). Recently this structure can be transformed into martensite if the material is submitted for reheating or to the stress field, causing distortion to its body. This non-tempered martensite can cause cracks, especially in complex shape tools made of high alloy steel (Heberling, 1992). Subzero processing will be changed by a large number of residual Austenite reaches Mf line, giving greater dimensional stability in the tool microstructure. The main variables during heat treatment have a great influence on the results. Studies done in steel equivalent to M2, changing the cryogenic cycle have quantified the precipitated particles and verified their effect on the properties of the material (Alexandru et al., 1990). Their study involved seven steel samples, each of which was subjected to different heating and cooling (up to -70°C) cycles. (Barron, 1982) after low-temperature treatment of several materials, including M2 high-speed steel, at -84°C (holding it at this temperature for 24 hours), compared to conventional heat-treated steel (quenching and tempering), a significant improvement in wear resistance was observed in the sliding wear test (Moore, 1974). When the temperature of the low-temperature treatment is further reduced to -196°C, the wear resistance is further improved. (Yun et al., 1998) verified the change in the microstructure of M2 high-speed steel material at different periods of -196°C cryogenic treatment. (Dong et al., 1998) a detailed study of the effect of changing the deep solidification and tempering cycle on high-speed steel, and concluded that the improved wear resistance of Tool Steel is due to the elimination of residual austenite and nucleation sites, which precipitated a large number of empirical studies have shown that low-temperature treatment can improve the high-speed steel and carbide cutting. Here the state of art is comparison between the Taguchi ARAS and other algorithm, In general, the main advantages of multi-criteria Decision Making (MCDM) can be summarized as follows: the ability to analyze complex problems, the ability to add quantitative and qualitative standards to the evaluation process, the ability to make good evidence, the ability to engage actively for the factors decision-making in the decision-making process (Barron, 1999), (S. P. Sundar Singh Sivam et al., 2016), (S. P. Sundar Singh Sivam et al., 2017), (S. P. Sundar Singh Sivam et al., 2018), (S. P. Sundar Singh Sivam et al., 2019) Flexible scientific methods in decision-making. According to ARAS, the newly proposed method, the value of the utility function determines the efficiency of a viable complex alternative which is directly proportional to the relative effect of the values and weights of the main criteria taken into account in the project. Alternatives can be prioritized based on the value of the instrument's function. It is, therefore, appropriate to evaluate and organize decision alternatives when using this method. The degree of the alternative instrument is determined by comparing the variant, which is analyzed, with the best optimal option. It can be argued that the best alternative relationship can be used in cases where it is attempted to organize alternatives and to find ways to improve alternative projects. It is difficult to assess the impact of different methods to solve the problem. According to ARAS, the new proposed method, the value of a utility function that determines the efficiency of a complex alternative is directly proportional to the relative effect of the values and weights of the main criteria taken into account in the project. Alternatives can be prioritized based on the value of the instrument's function. It is, therefore, appropriate to evaluate and organize decision alternatives when using this method. The degree of the alternative instrument is determined by comparing the variant, which is analyzed, with the best optimal option. It can be argued that the best alternative relationship can be used when looking for alternatives to arrange and find ways to improve alternative projects. In conclusion, the ARAS method has a promising future in the field of construction engineering as it provides a methodological basis for decision support. In this study, we give a basic guiding principle, that is, drilling parameters for machining and inspection of geometric dimensions and tolerances, surface roughness and tool wear methods, and are validated by the ARAS model and ANOVA on cryogenic treatment will be beneficial for future applications in both the manufacturing industry and the academic environment.

2. METHODOLOGY

A typical MCDM problem involves the task of ranking a limited number of alternative solutions, each of which is clearly described by different decision criteria to be considered simultaneously. According to the ARAS method, the value of the utility function, which determines the complex relative efficiency of a viable alternative, is proportional to the relative influence of the values and weights of the main criteria considered in the project. The first stage is the formation of the decision matrix (DMM). MDM for problems of discrete optimization any solvable by the following DMM of preferences for m feasible alternatives (rows) rated on n sign full criteria (columns) shown in equation (1) to equation (10).

$$X = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

$where\ i = \overline{0,m}\,; j = \overline{1,n}\,;$

where m – number of alternatives, n – number of criteria describing each alternative, xij – value representing the performance value of the i alternative in terms of the j criterion, *x0j* – optimal value of j criterion.

If optimal value of j criterion is unknown, then:

$$x_{oj} = \max_i x_{ij} \ \ if \ \max_i x_{ij} \ \ is\ preferable; \quad (2)$$

$$x_{0j} = \min_i x^*_{ij} \ \ if \ \min_i x^*_{ij} \ \ is\ preferable; \quad (3)$$

Normally, the yield values *xij* and the weights *wj* are shown as DMM entries. The system of criteria, as well as the initial values and the weights of the standards, are determined by experts. The information can be corrected by the interested parties taking into account their objectives and opportunities. The alternatives are then prioritized in several stages. In general, standards have different dimensions. The purpose of the next stage is to receive weighted values without dimensions of comparative criteria. To avoid difficulties derived from the different dimensions of the standards, the relationship is used for the optimal value. There are different theories that describe the relationship to the optimal value. However, the values are set in the interval [0; 1] or in the interval [0; ∞] applying the DMM standardization. In the second stage, the initial values of all the criteria are normalized; the xij values are determined for the regular decision-making matrix X.

$$\bar{X} = \begin{bmatrix} \bar{x}_{01} & \cdots & \bar{x}_{0j} & \cdots & \bar{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{i1} & \cdots & \bar{x}_{ij} & \cdots & \bar{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \cdots & \bar{x}_{mj} & \cdots & \bar{x}_{mn} \end{bmatrix} \quad (4)$$

Where, $i = \overline{0,m}\,; j = \overline{1,n}\,;$

The criteria, whose preferable values are maxima, are normalized as follows:

$$\overline{x_{\iota J}} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \quad (5)$$

The criteria, whose preferable values are minima, are normalized by applying a two-stage procedure:

$$x_{ij} = \frac{1}{x_{ij}^{*}}\,; \overline{x_{\iota J}} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \quad (6)$$

When the dimensionless values of the criteria are known, all the criteria, originally having different dimensions, can be compared. The third stage is defining normalized-weighted matrix –. It is possible to evaluate the criteria with weights 0 <w_j< 1. Only well-founded weights should be used because weights are always subjective and influence the solution. The values of weight w_j are usually determined by the expert evaluation method. The sum of weights *wj* would be limited as follows:

$$\sum_{j=1}^{n} w_j = 1 \quad (7)$$

$$\hat{X} = \begin{bmatrix} \hat{x}_{01} & \cdots & \hat{x}_{0j} & \cdots & \hat{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{i1} & \cdots & \hat{x}_{ij} & \cdots & \hat{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \cdots & \hat{x}_{mj} & \cdots & \hat{x}_{mn} \end{bmatrix} i = \overline{0,m}\,; j = \overline{1,n}\,; (8)$$

Normalized-weighted values of all the criteria are calculated as follows:
$\hat{x}_{ij} = \bar{x}_{ij} w_j \,; i = \overline{0,m}\,,$
Where w_j is the weight (importance) of the j criterion and xij is the normalized rating of the j criterion.
The following task is determining the values of optimality function:

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij} \;;\; i = \overline{0,m}\,, \quad (9)$$

where *Si* is the value of optimality function of i alternatives.
The biggest value is the best, and the least one is the worst. Taking into account the calculation process, the optimality function Si has a direct and proportional relationship with the values x_{ij} and weights w_j of the investigated criteria and their relative influence on the final result. Therefore, the greater the value of the optimality function *Si*, the more effective the alternative. The priorities of alternatives can be determined according to the value S_i.
Consequently, it is convenient to evaluate and rank decision alternatives when this method is used.
The degree of the alternative utility is determined by a comparison of the variant, which is analyzed, with the ideally best one S_0. The equation used for the calculation of the utility degree K_i of an alternative ai is given below:

$$K_i = \frac{S_i}{S_0} \;;\; i = \overline{0,m}\,, \quad (10)$$

where S_i and S_0 are the optimality criterion values, obtained from equations above.
It is clear that the calculated values K_i are in the interval [0, 1] and can be ordered in an increasing sequence, which is the wanted order of precedence. The complex relative efficiency of the feasible alternative can be determined according to the utility function values.
Analysis of variance: Analysis of variance (ANOVA) using the Taguchi technique, can be an accurate basis for not allowing the interpretation of pre-training. In the course of this study, there are three main controlled variables, i.e., three measurements, e.g., cutting Speed (3000/ 4500/ 6000rpm), feed (0.1/ 0.2/ 0.3mm/min) and cryogenic Treated drilling tool (1/2/3) which are used for ANOVA. The strength of their cooperation is determined on the basis of preliminary information through multidimensional research. In the middle of this study, using the Taguchi methodology, the L18 Orthogonal matrix is required for minimum geometric size and tolerance, surface roughness (Ra), tool wear. Specify the degree of probability, given the recommendations of Taguchi inside a larger or smaller S/N ratio for the answer is better.
Cryo-treatment Procedure: The drill bits utilized for the study were made to undergo three different conditions: cryogenic treatment with two tempering cycles, cryogenic treatment with one tempering cycle and only cryogenic treatment without any tempering cycles. The cryogenic treatment was carried out at a soaking temperature of -193°C and at a descend rate of 0.4°C/min. The drill bits were soaked for a period of 27hrs. After the cryogenic part was over, the drill bits were tempered at a temperature of 150°C at a rate of 4h/cycle. The time of ascend used was 28hrs. In

Figure 1, the graph of tool number 1 is shown which is not tempered and cryogenically treated. Figure 2 shows the graph of tool number 2, which is tempered once and Figure 3 shows the graph of tool number 3, which is tempered twice. The schematic diagrams of the process are shown in Figure 4 and Figure 5.

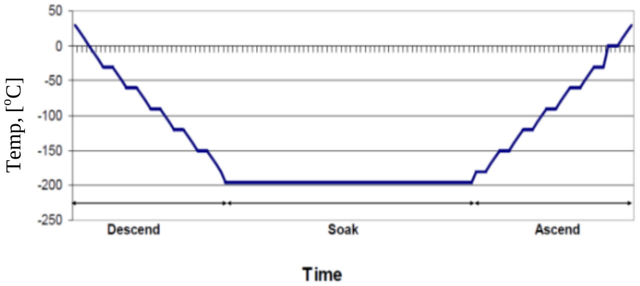

Fig. 1. Treatment for tool 1

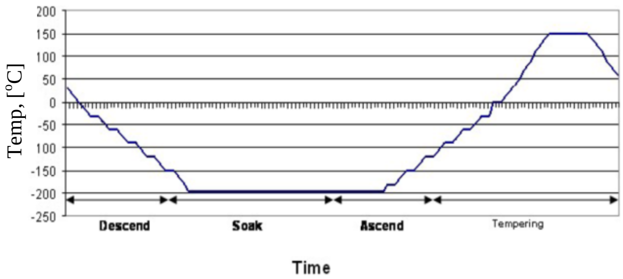

Fig. 2. Treatment for tool 2

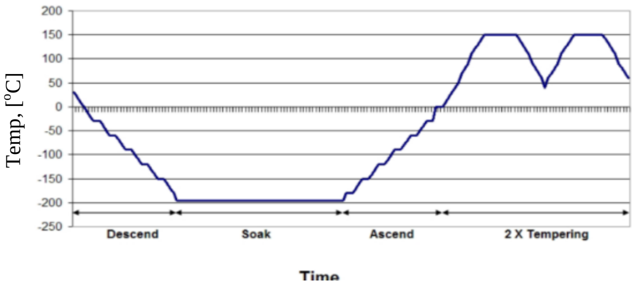

Fig. 3. Treatment for tool 3

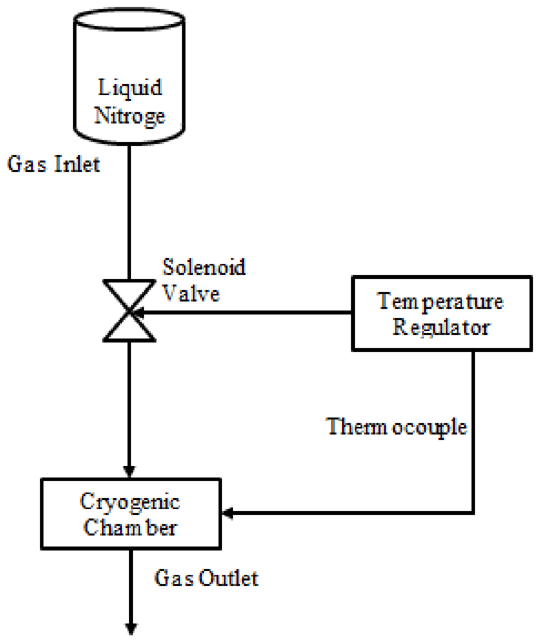

Fig. 4. Schematic diagram of cryogenic Drilling

To verify the effect of the cryogenic HSS drill, they have undergone a drilling process and have been compared with different Cryogenic HSS drilling tools. The AM60 was used, and the drilling was done in VMC manufactured by Lakshmi Works Machine LV45. Due to the choice of tool diameter of 4mm, operating parameters were used such as the cutting speed, feed speed and Drill Bits for several HSS drilling tools treated according to the dimensions and engineering tolerance, tool wear, roughness of the surface during the operation. Using input parameters, the Taguchi L9 experimental range was designed using the ARASS model from Taguchi and the experiment was performed for drilling tools treated with HSS, each of 180 seconds. Deviation from perpendicularity (mm), Deviation from concentricity (mm), and Deviation from diameter (mm) was measured by coordinate measuring machine (CMM), deviation from cylindricity (mm) was measured by (at least two circles over the hole), surface roughness was measured by (Talysurf), tool wear was measured by (Tool presetter), as shown in Table 1 and Table 2. The results were analyzed using Taguchi's ARASS to determine the individual effect of the input parameters on different output responses.

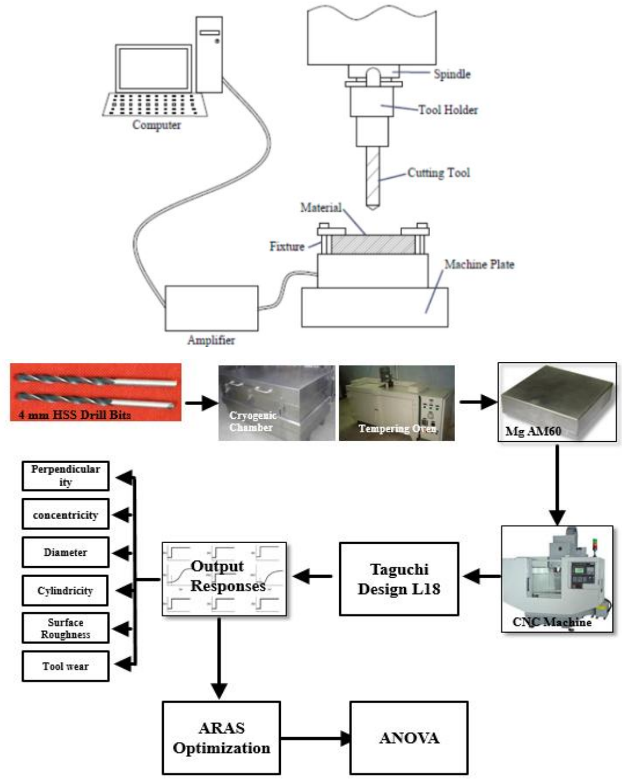

Fig 5. Schematic Diagram for Experimental Setup

Table 1. Process parameter Design

Parameters	**Unit**	**Levels**		
		1	**2**	**3**
Cutting Speed – IP 1	[rpm]	3000	4500	6000
Feed - IP 2	[mm/rev]	0.1	0.2	0.3
Treated Tool – IP 3	-	1	2	3

Table 2. Initial decision-making matrix X

Symbol	Type	Criterion
C1	1	Deviation from perpendicularity [mm]
C2	1	Deviation from concentricity [μm]
C3	1	Deviation from diameter [mm]
C4	1	Deviation from Cylindricity [μm]
C5	-1	Surface Roughness [μm]
C6	-1	Tool wear [μm]

3. RESULTS AND DISCUSSIONS

The measurement results are tabulated in Table 3, and Table 4, and the normalized values in Table 5 and Table 6.

Table 3. Measurement results

S.NO	Feed (f) [mm/rev]	Treated Tool	Cutting speed [rpm]	C1	C2	C3	C4	C5	C6
1	0.1	1	3000	1.71	116.63	1.71	116.63	1.88	127.88
2	0.1	1	4500	1.49	75.12	1.49	75.12	1.59	80.04
3	0.1	1	6000	2.68	208.87	2.68	208.87	3.54	276.00
4	0.1	2	3000	1.76	110.86	1.76	110.86	1.94	122.36
5	0.1	2	4500	1.18	67.20	1.18	67.20	1.21	69.00
6	0.1	2	6000	3.04	38.50	3.04	38.50	4.65	58.88
7	0.1	3	3000	1.64	79.69	1.64	79.69	1.78	86.48
8	0.2	3	4500	0.34	76.83	0.34	76.83	0.32	72.68
9	0.2	3	6000	1.50	62.98	1.50	62.98	1.60	67.16
10	0.2	1	3000	2.39	59.80	2.39	59.80	2.94	73.60
11	0.2	1	4500	2.12	47.27	2.12	47.27	2.47	55.20
12	0.2	1	6000	1.47	111.70	1.47	111.70	1.56	118.68
13	0.3	2	3000	1.23	64.16	1.23	64.16	1.27	66.24
14	0.3	2	4500	2.55	44.68	2.55	44.68	3.26	57.04
15	0.3	2	6000	2.00	63.48	2.00	63.48	2.29	72.68
16	0.3	3	3000	1.50	89.72	1.50	89.72	1.60	95.68
17	0.3	3	4500	1.83	301.07	1.83	301.07	2.04	335.80
18	0.3	3	6000	1.44	89.59	1.44	89.59	1.52	94.76

Table 4. Measurement results (initial decision-making matrix X)

Weights of criteria	0.21	0.16	0.26	0.17	0.12	0.08
Kind of criteria	1	1	1	1	-1	-1
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
A1	1.71	116.63	1.71	116.63	1.88	127.88
A2	1.49	75.12	1.49	75.12	1.59	80.04
A3	2.68	208.87	2.68	208.87	3.54	276.00
A4	1.76	110.86	1.76	110.86	1.94	122.36
A5	1.18	67.20	1.18	67.20	1.21	69.00
A6	3.04	38.50	3.04	38.50	4.65	58.88
A7	1.64	79.69	1.64	79.69	1.78	86.48
A8	0.34	76.83	0.34	76.83	0.32	72.68
A9	1.50	62.98	1.50	62.98	1.60	67.16
A10	2.39	59.80	2.39	59.80	2.94	73.60
A11	2.12	47.27	2.12	47.27	2.47	55.20
A12	1.47	111.70	1.47	111.70	1.56	118.68
A13	1.23	64.16	1.23	64.16	1.27	66.24
A14	2.55	44.68	2.55	44.68	3.26	57.04
A15	2.00	63.48	2.00	63.48	2.29	72.68
A16	1.50	89.72	1.50	89.72	1.60	95.68
A17	1.83	301.07	1.83	301.07	2.04	335.80
A18	1.44	89.59	1.44	89.59	1.52	94.76

Table 5. Normalized values (normalized decision-making matrix X)

Weights of criteria	0.21	0.16	0.26	0.17	0.12	0.08
Kind of criteria	1	1	1	1	-1	-1
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
0-Optimal Value	0.0870	0.1498	0.0870	0.1498	0.2066	0.0779
A1	0.0490	0.0580	0.0490	0.0580	0.0352	0.0336
A2	0.0428	0.0374	0.0428	0.0374	0.0416	0.0538
A3	0.0768	0.1040	0.0768	0.1040	0.0187	0.0156

A4	0.0504	0.0552	0.0504	0.0552	0.0341	0.0352
A5	0.0338	0.0334	0.0338	0.0334	0.0545	0.0624
A6	0.0870	0.0192	0.0870	0.0192	0.0142	0.0731
A7	0.0469	0.0397	0.0469	0.0397	0.0372	0.0498
A8	0.0097	0.0382	0.0097	0.0382	0.2066	0.0592
A9	0.0430	0.0313	0.0430	0.0313	0.0413	0.0641
A10	0.0685	0.0298	0.0685	0.0298	0.0225	0.0585
A11	0.0607	0.0235	0.0607	0.0235	0.0267	0.0779
A12	0.0422	0.0556	0.0422	0.0556	0.0423	0.0363
A13	0.0352	0.0319	0.0352	0.0319	0.0521	0.0650
A14	0.0731	0.0222	0.0731	0.0222	0.0203	0.0754
A15	0.0573	0.0316	0.0573	0.0316	0.0289	0.0592
A16	0.0430	0.0447	0.0430	0.0447	0.0413	0.0450
A17	0.0525	0.1498	0.0525	0.1498	0.0324	0.0128
A18	0.0411	0.0446	0.0411	0.0446	0.0436	0.0454

Table 6. Weighted-normalized values (weighted-normalized decision-makingmatrix) and solution results

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**S**	**K**	**Ranking**
0-Optimal Value	0.0183	0.0240	0.0226	0.0255	0.0248	0.0062	0.1214	1.0000	
A1	0.0103	0.0093	0.0127	0.0099	0.0042	0.0027	0.0491	0.4047	6
A2	0.0090	0.0060	0.0111	0.0064	0.0050	0.0043	0.0417	0.3439	15
A3	0.0161	0.0166	0.0200	0.0177	0.0022	0.0012	0.0739	0.6087	2
A4	0.0106	0.0088	0.0131	0.0094	0.0041	0.0028	0.0488	0.4020	7
A5	0.0071	0.0054	0.0088	0.0057	0.0065	0.0050	0.0385	0.3170	18
A6	0.0183	0.0031	0.0226	0.0033	0.0017	0.0058	0.0548	0.4513	3
A7	0.0098	0.0063	0.0122	0.0067	0.0045	0.0040	0.0436	0.3589	12
A8	0.0020	0.0061	0.0025	0.0065	0.0248	0.0047	0.0467	0.3848	8
A9	0.0090	0.0050	0.0112	0.0053	0.0050	0.0051	0.0406	0.3348	16
A10	0.0144	0.0048	0.0178	0.0051	0.0027	0.0047	0.0494	0.4070	5
A11	0.0127	0.0038	0.0158	0.0040	0.0032	0.0062	0.0457	0.3768	10
A12	0.0089	0.0089	0.0110	0.0095	0.0051	0.0029	0.0461	0.3801	9
A13	0.0074	0.0051	0.0092	0.0054	0.0063	0.0052	0.0385	0.3176	17
A14	0.0153	0.0036	0.0190	0.0038	0.0024	0.0060	0.0502	0.4133	4
A15	0.0120	0.0051	0.0149	0.0054	0.0035	0.0047	0.0456	0.3754	11
A16	0.0090	0.0071	0.0112	0.0076	0.0050	0.0036	0.0435	0.3584	13
A17	0.0110	0.0240	0.0136	0.0255	0.0039	0.0010	0.0790	0.6510	1
A18	0.0086	0.0071	0.0107	0.0076	0.0052	0.0036	0.0429	0.3534	14

According to the given data on the criteria describing the minimum geometric dimension and tolerance, surface roughness (Ra), tool wear can be made. The studies performed help to identify the inside climate parameters of the workplace, which do not meet specifications. The data obtained can also be used for developing and implementing measures aimed at increasing the product quality for the benefits of customers. The results obtained (quality ratio with an optimal parameter alternative according to its rank) represent inside climate characteristics with some error. The study of the optimum process parameter of the obtained data with the values provided by the hygienic norms allowed us to state that most of the investigated parameters do not meet the current specifications. Priority order of the investigated rooms can be represented as: A17>A3>A6>A14>A10>A1>A4>A8>A12>A11>A15>A7>A16>A18>A2>A9>A13>A5. It means that the best process parameter is in drilling operation 17, and the worst process parameter is in drilling operation 4. It can be stated that in room 17 the process parameter is in drilling operation makes only 65% of optimally, and in the worst room the ratio with an optimally balanced process parameter is in drilling Operation is only of 31.6%.

From Table 7, it was found that the treated tool is the most important factor affecting perpendicularity, followed by the speed of the spindle and the feed.

Table 7. ANOVA on deviation from perpendicularity [mm]

SOV	**SOS**	**DOF**	**MS**	**F**	**Ftable**	**%**
IP 1	-47.06	2	-23.5306	-11765.3	4.2	19%
IP 2	-100.91	2	-50.4534	-25226.7	4.2	40%
IP 3	-102.51	2	-51.25473333	-25627.36667	4.2	41%
Error	0.002	27	0.002			
SSG	-250.4774667					

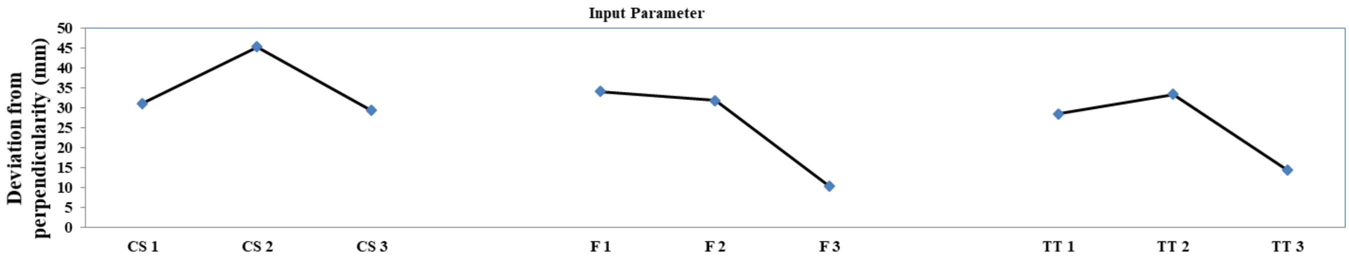

Fig 6. Effects on deviation from perpendicularity [mm]

From Figure 6, it can be inferred that cutting speed of 4500rpm, feed of 0.1mm/rev, and treated tool of 3 is most optimum conditions for obtaining minimum deviation of perpendicularity.

From Table 8, it was found that the spindle speed is the most important factor affecting the concentricity, followed by the treated tool and the feed.

Table 8. ANOVA on deviation from concentricity (mm)

SOV	SOS	DOF	MS	F	F table	%
IP 1	468916.25	2	234458.1248	117229062.4	4.2	41%
IP 2	323986.34	2	161993.1678	80996583.89	4.2	28%
IP 3	355483.83	2	177741.9145	88870957.25	4.2	31%
Error	0.002	27	0.002			
SSG	1148386.414					

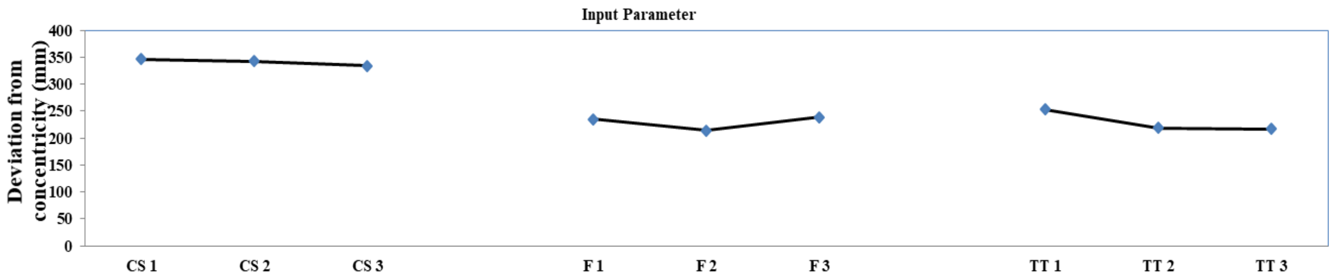

Fig 7. Effects on deviation from concentricity [mm]

From Figure 7, it can be inferred that cutting speed of 6000rpm, feed of 0.3mm/rev, and treated tool of 1 is most optimum conditions for obtaining minimum deviation of concentricity.

From Table 9, it was found that the treated tool was the most important factor affecting the diameter, followed by the feed rate and the spindle speed.

Table 9. ANOVA on deviation from diameter [mm]

SOV	SOS	DOF	MS	F	F table	%
IP 1	-47.06	2	-23.5306	-11765.3	4.2	19%
IP 2	-100.91	2	-50.4534	-25226.7	4.2	40%
IP 3	-102.51	2	-51.25473333	-25627.36667	4.2	41%
Error	0.002	27	0.002			
SSG	-250.4774667					

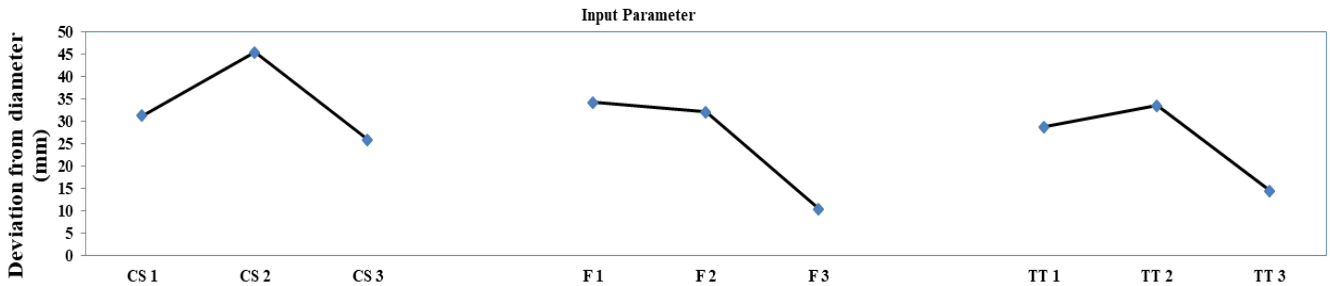

Fig 8. Effects on deviation from the diameter [mm]

From Figure 8, it can be inferred that cutting speed of 4500rpm, Feed of 0.1mm/rev, and treated tool of 2 is most optimum conditions for obtaining minimum deviation from the diameter.

From Table 10, it was found that the spindle speed is the most important factor affecting the cylindricity, followed by the treated tool and the feed.

Table 10. ANOVA on deviation from cylindricity [mm]

SOV	SOS	DOF	MS	F	F table	%
IP 1	468916.25	2	234458.1248	117229062.4	4.2	41%
IP 2	323986.34	2	161993.1678	80996583.89	4.2	28%
IP 3	355483.83	2	177741.9145	88870957.25	4.2	31%
Error	0.002	27	0.002			
SSG	1148386.414					

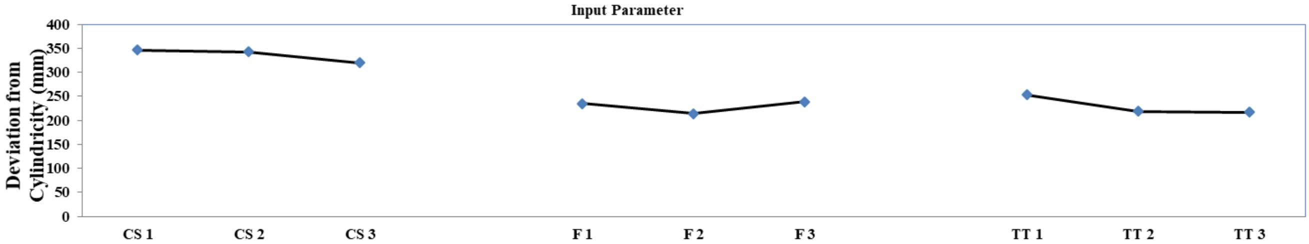

Fig 9. Effects on deviation from cylindricity [mm]

From Figure 9, it can be inferred that cutting speed of 6000rpm, Feed of 0.3mm/rev, and treated tool of 1 is most optimum conditions for obtaining minimum deviation from cylindricity.

From Table 11, it was found that the treated tool is the most important factor affecting the roughness of the surface, followed by the feed rate and the spindle speed.

Table 11. ANOVA on surface roughness [µm]

SOV	SOS	DOF	MS	F	F table	%
IP 1	-100.19	2	-50.09494683	-25047.47342	4.2	22%
IP 2	-171.54	2	-85.76798017	-42883.99008	4.2	38%
IP 3	-175.12	2	-87.5600135	-43780.00675	4.2	39%
Error	0.002	27	0.002			
SSG	-446.845881					

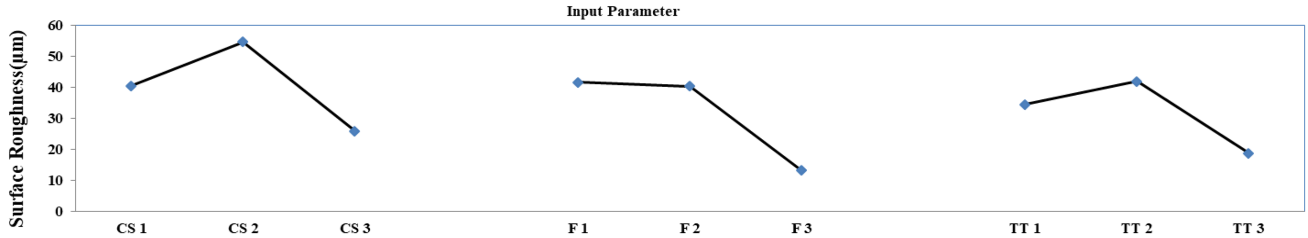

Fig 10. Effects on surface roughness [µm]

From Figure 10, it can be inferred that cutting speed of 4500rpm, feed of 0.2mm/rev, and treated tool of 2 is most optimum conditions for obtaining minimum surface roughness (µm).

From Table 12, it was found that the spindle speed is the most important factor that affects the wear of the tool, followed by the treated tool and the feed.

Table 12. ANOVA on tool wear [µm]

SOV	SOS	DOF	MS	F	F table	%
IP 1	602391.08	2	301195.5396	150597769.8	4.2	41%
IP 2	414919.69	2	207459.843	103729921.5	4.2	28%
IP 3	463613.64	2	231806.8212	115903410.6	4.2	31%
Error	0.002	27	0.002			
SSG	1480924.407					

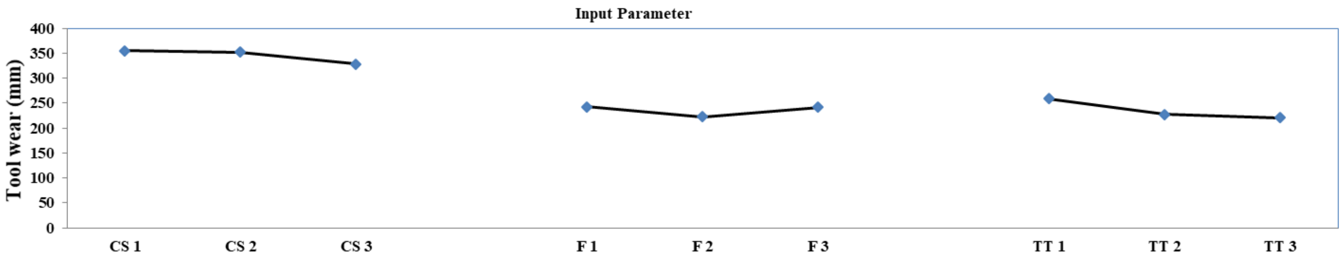

Fig. 11. Effects on tool wear [mm]

From Figure 11, it can be inferred that cutting speed of 4500rpm, Feed of 0.3mm/rev, and treated tool of 1 is most optimum conditions for obtaining minimum tool wear (mm).

From Table 13, spindle speed, feed and treated tool is found to be the most significant factors affecting the ARAS grade.

Table 13. ANOVA on ARAS grade

SOV	SOS	DOF	MS	F	F table	%
IP 1	-678.86	2	-339.429483	-169714.7415	4.2	33%
IP 2	-682.35	2	-341.1768697	-170588.4349	4.2	33%
IP 3	-682.25	2	-341.1274142	-170563.7071	4.2	33%
Error	0.002	27	0.002			
SSG	-2043.467534					

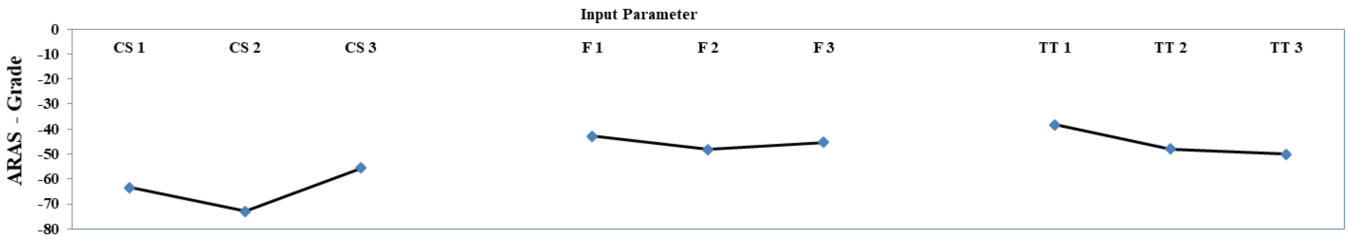

Fig. 12. Effects on ARAS grade

From Figure 12, it can be inferred that cutting speed of 6000rpm, feed of 0.3mm/rev, and treated tool of 1 is most optimum conditions for obtaining ARAS grade.

4. CONCLUSIONS

The Taguchi Additive Ratio ASsessment (ARAS) method was performed in AM60 magnesium alloy using 4mm HSS class drilling tool and the geometric dimension, surface roughness (Ra) and tool wear was obtained at different cutting conditions by this method. This study shows that most optimum conditions for minimum deviation of perpendicularity was obtained at the cutting speed of 4500rpm, feed of 0.1mm/rev, and treated tool of 3. The optimum conditions for minimum deviation from the diameter was obtained at the cutting speed of 4500rpm, feed of 0.1mm/rev and treated tool of 2. The minimum deviation of concentricity was obtained at the cutting speed of 6000rpm, feed of 0.3mm/rev and treated tool of 1. The minimum deviation from cylindricity was obtained at cutting speed of 6000rpm, feed of 0.3mm/rev and treated tool of 1. The most optimum conditions for minimum surface roughness (µm) was obtained at cutting speed of 4500rpm, feed of 0.2mm/rev and treated tool of 2. The most optimum conditions for minimum tool wear (mm) was obtained at cutting speed of 4500rpm, feed of 0.3mm/rev and treated tool of 1.

Finally the order of priority for the chambers tested can be summarized as follows: A17>A3>A6>A14>A10>A1>A4>A8>A12>A18>A2>A9>A5>A5. The best process parameter was found in drilling operation 17 with the optimum percentage 65% and the worst process parameter was found in drilling operation 4 with the optimum percentage 31% as per ARAS method.

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