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Multi-Criteria Selection of the Optimal Parameters for High-Speed Machining of Aluminum Alloy Al7075 Thin-Walled Parts

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Abstract: Thin-walled parts made of aluminum alloy are mostly used as structural elements in the aerospace, automobile, and military industries due to good homogeneity, corrosion resistance, and the excellent ratio between mechanical properties and mass. Manufacturing of these parts is mainly performed by removing a large volume of material, so it is necessary to choose quality machining parameters that will achieve high productivity and satisfactory quality and accuracy of machining. Using the Taguchi methodology, an experimental plan is created and realized. Based on its results and comparative analysis of multi-criteria decision making (MCDM) methods, optimal levels of machining parameters in high-speed milling of thin-walled parts made of aluminum alloy Al7075 are selected. The varying input parameters are wall thickness, cutting parameters, and tool path strategies. The output parameters are productivity, surface quality, dimensional accuracy, the accuracy of forms and surface position, representing the optimization criteria. Selection of the optimal machining parameter levels and their ranking is realized using 14 MCDM methods. Afterward, the obtained results are compared using correlation analysis. At the output, integrative decisions were made on selecting the optimal level and rank of alternative levels of machining parameters.

Keywords: thin-walled parts; aluminum alloy Al7075; high speed milling; optimization of machining parameters; MCDM methods; correlation analysis

1. Introduction

The modern market of specialized products requires materials with high mechanical properties, small mass, relatively low price, and good machinability, which is all contained in aluminum alloys [1]. Thin-walled parts of aluminum alloys are very important structural components in the aerospace, automobile, and military industries, but they are often used in toolmaking and other electromechanical industry branches [2,3].

In parallel with the increase in market requirements for thin-walled components of aluminum alloys, numerous studies are being realized which are oriented towards:

- Design optimization to reduce mass, deformations and vibrations, increase load capacity, and strength

- Optimization of manufacturing process planning to increase productivity, cost-effectiveness, the dimensional accuracy, accuracy of forms and surface position, machining quality, etc., which is the main research subject in this paper.

Thin-walled parts of Al alloys can be obtained by casting, injection molding, material removal technologies, etc. Manufacturing of these parts is most often realized by milling, during which a large volume of material is removed, which can amount up to 95% of the initial mass of raw material [4,5]. Therefore, using appropriate high-speed machining parameters, it is necessary to achieve high productivity while also maintaining the required machining accuracy and quality. On the other hand, due to the low stiffness of thin-walls, it is also recommended to avoid the appearance of vibrations and deformations, which can cause machining errors, low quality, and the appearance of scrap [6–9]. The main causes for the appearance of these errors in the literature are the type of material, elements of machining system (machine, tool, fixtures), cutting parameters, machining strategies, metalworking fluids and coolants, wall thickness, and others [2,5,10–15]. By analyzing numerous research studies, influential machining parameters for thin-walled structures are systematized and represented in Figure 1.

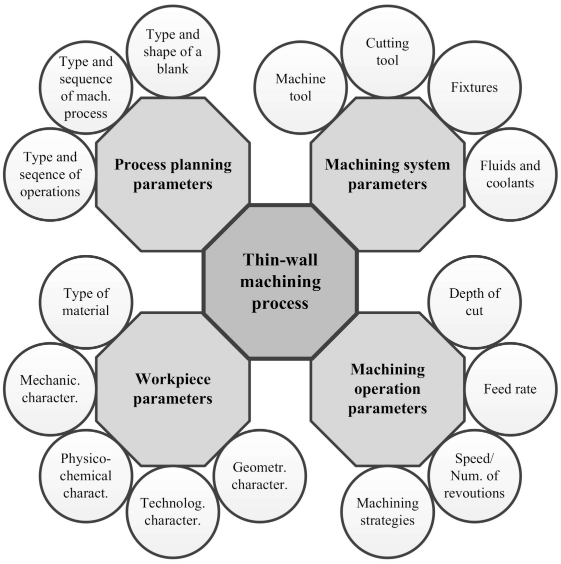


Figure 1. Influential machining parameters for thin-walled parts.

The main groups of machining parameters for thin-walled parts are the following:

- Process planning parameters: Type and shape of a blank (casting, bar, sheet metal, etc.), Type and sequence of process operations (casting, cutting, heat treatment, etc.), Type and sequence of machining operations (face and plane milling, rough and soft milling, etc.)
- Machining system parameters: Machine tool (stiffness, accuracy, available cutting parameters, etc.), Cutting tool (type, material, geometry, number of cutting edges, specific cutting edge angles, etc.), Fixtures (type, method, and place of positioning, clamping force, etc.), Metalworking fluids and coolants (type, concentration, purity, supply method, pressure)
- Workpiece parameters: Type of material, Mechanical characteristics (hardness, strength, elasticity, toughness, etc.), Physicochemical characteristics (structure, chemical composition, density, thermal characteristics, corrosion resistance, etc.), Technological characteristics (machinability parameters), Geometric characteristics (shape: linear, triangular, rectangular, hexagonal and complex; wall-thickness to the wall-height ratio: small height-to-thickness ratio <15:1, moderate height-to-thickness ratio <30:1, very large height-to-thickness ratio ≥30:1; the accuracy of measures, the accuracy of forms and surface position; surface quality, etc.) and
- Machining operation parameters: depth of cut, feed, cutting speed/number of revolutions, tool path strategies.

Authors in [16,17] investigated the influence of wall thickness, milling forces, and cutting tool position on the deformations of thin-walls and the appearance of geometric errors. The results from [16] show that the machining parameters can be selected for each pass to achieve milling efficiency and accuracy, while the results from [17] predict the definition of remnant material in order to reduce deformations and achieve high machining quality. Yan et al. [18] proposed the machining strategy with maximal depth of cut from the considered range and with the respect to the threshold of the cutting force. Efficiency of the proposed methodology was tested on the basis of simulation and experiments and the obtained results showed the reduction in machining time and surface error.

The study in [19] considers the influence of clamping fixtures, operation sequence, selected tool path strategy, and cutting parameters on plastic/elastic deformations during the machining process using FEM analysis and CAM software. The proposed model performs a computationally efficient transient thermo-mechanical coupled field milling simulation, predicts the workpiece non-linear behavior during machining due to its changing geometry, allows the modelling of the effects of initial residual stresses on part deformations and integrated analytical machining load - cutting force and shear plane temperature. A model of deformations of thin-walled structures in the milling process and prediction of machining errors are investigated in [20,21]. In [20], a new model is proposed to predict surface form errors caused by milling force during the five-axis flank milling process. The results showed that the surface deformation error of thin-walled structures is affected together by the instantaneous milling force and the local stiffness of the workpiece. On the other hand, in the paper [21] a three-dimensional finite element model was established for the milling of thin-walled parts, that predicts the elastic deformation law of the thin-walled blade.

Sapthagiri and Rao [22] used the Taguchi method to experimentally examine the significance of machining parameters (cutting speed, feed, depth of cut, a width of cut, tool path layout) and the influence of coolants on the reduction in tool temperature, as influential parameters on the deformation during machining. The optimum parameters which influence distortion were identified. By checking the samples machining with different tools and different speeds the warpage of the components are very less. Authors in [23] emphasized the influence of cutting parameters on the cutting forces and the surface roughness during face milling of aluminum alloy 7075 obtained by the new semi-solid metal casting process. Results show that the optimal combination for the cutting force is the choice of a minimum level for all tested parameters, while for the surface roughness the cutting depth at the median level is the most preferable for the observed range.

Sridhar and Babu [24] investigated the influence of the material removal rate on the distortion of thin-walled parts of aluminum alloy by combining the following machining parameters: feed, cutting speed, depth of cut, and width of cut. They concluded that the increase of feed, depth of cut and width of cut lead to the increase of distortion of thin-walled structures. Also, the increase of material removal rate by increasing feed and speed instead of depth of cut and width of cut represents better solution for minimizing wall distortion. Qu et al. [25] optimized the milling parameters for thin-walled parts from the point of view of cutting forces, surface roughness, and material removal rate. The results showed that the cutting force and surface roughness increased with increasing feed per tooth and milling depth. On the other hand, the increase of spindle speed affected the increase of cutting force as well as the decrease of surface roughness.

Bolar et al. [26] researched the influence of feed rate, the number of flutes and machining strategies on surface finish, and deflection errors during machining of ultra-thin C shaped walls made of aluminum alloy. The authors concluded that a combined approach i.e., concave and convex machining with four fluted carbide end mill produced superior quality and precise thin-wall components. Shamsuddin et al. [27] compared milling cutting path strategies on surface finish, thickness accuracy, and machining time for thin-walled aluminum alloys. MasterCam X MR2 software was used to obtain the best tool path strategy. Experimental results showed that true spiral is the best machining strategy in terms of thickness accuracy but lack of surface roughness when compared to other machining strategies. However, concerning surface roughness and machining time, the parallel spiral strategy was more promising when compared to other strategies. Popma [28] developed a system for automated generative computer-aided process planning (CAPP) for thin-walled parts machined on high-speed CNC machines with a special emphasis on machining sequence and strategies for thin-walled parts while achieving accuracy and quality of machining.

Due to the low rigidity of the thin-walled structures, vibrations often occur during machining, which is divided into self-induced and forced vibrations [5]. Self-induced vibrations or chatter occur when the frequency response is induced by the machining process, i.e., due to friction in the tool-workpiece system, thermo-mechanical processes, or as a consequence of a regenerative effect. Forced vibrations or amplification occur when the stiffness of the part is not sufficient to maintain a constant chip thickness. The cutting tool bounces off the workpiece, producing vibrations at the same frequency as the main spindle and its components.

Machining parameters significantly affect the efficiency of the machining process but also its stability. In order to provide these criteria stability lobes diagrams (SLD) are used. Stability lobes diagrams represent areas of stability, i.e., areas of machining parameters where vibrations will not occur [29]. Authors in [30] studied the effect of VSR (Vibratory Stress Relief) on the deformations and residual stresses of Al 7075 thin-walled parts. They concluded that VSR improved the shape and size of material stability to a significant level by relieving induced residual stresses in thin-walled parts. In addition to static and dynamic models, there are also analytical models related to the development of new methods for predicting the behavior of systems based on frequency response and deformations resulting from cutting forces [31].

By analyzing the literature sources, it can be concluded that the field of machining of thin-walled parts has been the research subject of many researchers around the world for many years. Due to the specificity of the thin-walled part design, the machining parameters' influence is much more pronounced compared to the "normal" thick-walled parts. Optimization theory as a scientific discipline has a huge application in solving various engineering problems, where the application of appropriate methods finds the best solution for the selected optimization object for certain conditions based on one or more optimization criteria. Machining parameters are most often input variables that are optimized within the machining processes. For optimal parameters, those values are taken that give the best solution of the objective function. The selection and optimization of machining parameters are mostly realized using experimental research with the application of appropriate single and multi-criteria optimization methods, simulation techniques, and their combination.

This paper's main research subject is to determine the quality machining parameters in high-speed milling of linear thin-walled components made of aluminum alloy Al7075. To that end, using the standard Taguchi orthogonal sequence L_{27}, the experimental plan is created and realized. Based on its results and by applying MCDM methods, selecting the optimum machining parameter levels is achieved. At the input of the experimental design, the following parameters are varied: wall thickness (a), number of revolutions (n), feed rate (f), depth of cut (δ), and tool path strategies (TPS), while the output parameters are the following ones: machining time (T)/material removal rate (MRR), wall thickness deviation (Δa), flatness deviation (Δb), parallelism deviation (Δc), perpendicularity deviation (Δd) and surface roughness (Ra). These output parameters represent the optimization criteria, which are assigned weight coefficients based on the design and technological requirements of thin-walled parts. The selection of the optimum machining parameter levels and their ranking is realized using 14 chosen MCDM methods: GRA (Grey Relational Analysis), AHP (Analytic Hierarchy Process), MOORA (Multi-Objective Optimization Method by Ratio Analysis), TOPSIS (Technique for Order Performance by Similarity to Ideal Solution), ROV (Range Of Value), COPRAS (COmplex PRoportional Assessment of alternatives), ARAS (Additive Ratio ASsessment), WASPAS (Weighted Aggregates Sum Product ASsessment), VIKOR (VIsekriterijumska optimizacija i KOmpromisno Resenje - in Serbian), OCRA (Operational Competitiveness Rating Analysis), EDAS (Evaluation based on Distance from Average Solution), MABAC (Multi-Attributive Border Approximation area Comparison), SAW (Simple Additive Weighting) and SPW (Simple Product Weighting). The obtained results are compared and methods that satisfy the pre-determined constraints of correlation coefficients are adopted using correlation analysis. Based on these results, the integrative and final solution of the optimal machining parameter levels is defined, and alternative solutions are ranked.

2. MCDM Problem and the Model of the Integrative Multi-Criteria Ranking of Alternatives

2.1. MCDM Problem

Designers often encounter the need to select the optimal solution concerning products, processes, resources, etc. [32,33]. In such situations, in addition to a large number of alternatives, a large number of criteria appear, which together make the problem of selection more complex. The appearance of several alternatives and criteria, some of which need to be maximized and some minimized, means that decisions should be made in conflicting conditions and that multi-criteria decision-making techniques should be applied to solve these complex tasks. These methods are based on scientific principles that efficiently determine the optimal solution [34,35].

Since the proposed decision-making problem refers to the limited number of known alternatives, the application of multiple-attribute decision making (MADM) is assumed. Numerous researchers and scientists have developed many MCDM methods, from intuitive to sophisticated analytical methods. These methods can be used to identify a single most suitable alternative, rank alternatives, select a limited number of alternatives, or simply to distinguish acceptable from unacceptable alternatives [32,34].

There are similarities and differences when dividing the decision-making process into phases, but they can generally be divided into the following ones:

1. Identifying and formulating a decision-making problem—an objective function;
2. Forming a decision-making model—determining a set of alternatives and criteria and collecting appropriate data;
3. Applying an MCDM method—determining weight coefficients, evaluating alternatives for selected criteria and evaluating alternatives;
4. Selecting the most acceptable alternative and/or ranking alternatives;
5. Correlation analysis and integrative selection of the most acceptable alternative and/or ranking of alternatives (in case of using several MCDM methods to solve the same problem);
6. Analyzing the obtained results.

MCDM is a scientific field that is growing rapidly and intensively, as evidenced by the numerous methods that have been developed so far and are still being developed [32,34,36–42]. In this paper, the following MCDM methods introduced by the following researchers are applied: GRA [43], AHP [44], MOORA [45], TOPSIS [46], ROV [47], COPRAS [48], ARAS [49], WASPAS [50], VIKOR [51], OCRA [52], EDAS [53,54], MABAC [55], SAW [56] and SPW [34]. The main characteristics of these methods are to be transparent and simple, provide a complete ranking of alternatives, ensure the use of minimum and maximum criteria, enable the use of quantitative and qualitative data, not to require expert knowledge in mathematics, and not to use specialized software [32,34,38].

In most papers, one or a few MCDM methods are used to select the optimal variant of products, processes, resources, materials, etc. When a large number of these methods are applied, it is necessary to compare them and make a final integrative decision about the selection of the optimal solution [34,57–59].

2.2. Model of the Integrative Multi-Criteria Ranking of Alternatives

By applying several different MCDM methods to the same problem, even the same decision-maker can obtain different results of alternative rankings which leads to the problem of conflicting decision results. To be able to statistically analyze these conflicts and select methods whose results will be the basis for deciding and selecting the optimal alternative and their rank, it is necessary to consider as many different methods as possible that would form a sufficient sample [34,57–59].

To reduce the risk of making wrong decisions, a large number of different MCDM methods are applied in this paper. Through an iterative procedure, it is necessary to choose at least two methods that will form the basis for integrative decision making on selecting the optimal alternative and rank of alternatives. In the proposed case, these methods are chosen using the following methodology which is realized through several iterations based on the appropriate parameters of correlation with the limit values.

2.2.1. First Iteration

In the first iteration, the ranks of all applied MCDM methods are compared, and the values of Spearman's rank correlation coefficients (R_i), the total Kendall's rank correlation coefficient (W) as well as the average Spearman rank correlation coefficient (R) of all MCDM methods are determined, as well as standard deviations for all levels (σ_i), i.e., values of maximum and average standard deviation (σ_{max} and σ_{av}). These coefficients are compared with the limit-acceptable values, and if they are all within the allowed limits, no further iterations will be performed. On the other hand, the final solution—the ranks of alternative levels of a process plan's parameters can be formulated.

Spearman's Rank Correlation Coefficient (R_i)

Spearman's rank correlation coefficient (R_i) makes it possible to quantify the degree of correlation between any two sets of rank alternatives obtained by applying different MCDM methods and is calculated according to the Equation (1). Spearman's rank correlation coefficients (R_i) should be in the range between $0.9 \leq R_i \leq 1$ [60].

$$R_i = 1 - \frac{6\sum_{i=1}^{N} d_i^2}{N\left(N^2 - 1\right)} \tag{1}$$

where:

- N—sample size (number of alternatives to be ranked);
- X_i and Y_i—the calculation values of output coefficients for any two MCDM methods;
- x_i and y_i—the ranks of alternatives in the model obtained based on X_i and Y_i values;
- $d_i = (x_i - y_i)$—the difference between ranks of alternatives of two MCDM methods.

Kendall's Rank Correlation Coefficient

Kendall's rank correlation coefficient is used to determine the degree of correlation of the ranks of all alternatives when three or more MCDM methods are used for decision making, which corresponds to the case investigated in this paper. Kendall's rank correlation coefficient (W) is calculated using the Equation (2). Kendall's rank correlation coefficient should be in the range between $0.9 \leq W \leq 1$ [61]:

$$W = \frac{12 \cdot \sum_{i=1}^{k} T_j^2}{k^2 \cdot m(m^2 - 1)} - \frac{3(m+1)}{m-1} \tag{2}$$

where:

- T_j—the total sum of squares of ranks for each alternative;
- m—the number of alternatives to be ranked;
- k—the number of applied MCDM methods.

Average Spearman's Correlation Coefficient (R)

Average Spearman's rank correlation coefficient represents the correlation of all pairs of ranks of alternatives obtained by applying different MCDM methods within the decision model. The simplest equation for its determination is based on Kendall's W concordance coefficient, according to Equation (3). The average Spearman rank correlation coefficient (R) should be between $0.9 \leq R \leq 1$ [61].

$$R = \frac{k \cdot W - 1}{k - 1} \tag{3}$$

Standard Deviation

Standard deviation defines how much, on average, the elements of the sample deviate from the arithmetic mean. In the observed case, the standard deviation values by levels-alternatives (σ_i) are determined, and then the values of the maximum and average standard deviation (σ_{max} and σ_{av}) are determined. The average standard deviation should be between $\sigma_{av} \leq 1.5$ [60].

2.2.2. Second and Further Iterations

Within the second iteration, methods that do not meet the limit values of previously defined correlation coefficients are omitted from the further analysis, and the correlation coefficients are re-determined, as well as their comparison with the limit values.

The procedure is repeated until at least two MCDM methods that satisfy the correlation coefficients' set limit values are found. The more methods that meet the set conditions and the greater the degree of correlation of the applied methods, the better and more accurate the solution is. If the optimal solution is not found, it is necessary to apply other MCDM methods to satisfy the conditions of correlation analysis.

3. Materials and Methods

3.1. Defining the Optimization Task

The object of this research is a linear thin-walled structure of aluminum alloy with a wall thickness of a = 0.5–1.5 mm and a wall height of 30 mm, so the parts belong to the category of moderate height-to-thickness ratio <30:1 (for 1.5 mm wall thickness) and very large height-to-thickness ratio ≥30:1 (for 0.5 mm and 1mm wall thickness).Considering that many parameters affect the process of high-speed milling of thin-walled parts, recent experimental researches were conducted to determine their limit values and level of influence on specific output parameters—optimization criteria [62]. As a result of these investigations, the following input parameters were selected: wall thickness (a), number of revolutions (n), feed rate (f), depth of cut (δ), and tool path strategy (TPS) while the output parameters were measured and calculated: machining time (T) / material removal rate (MRR), wall thickness deviation (Δa), flatness deviation (Δb), parallelism deviation (Δc), perpendicularity deviation (Δd) surface roughness (Ra), Figure 2.

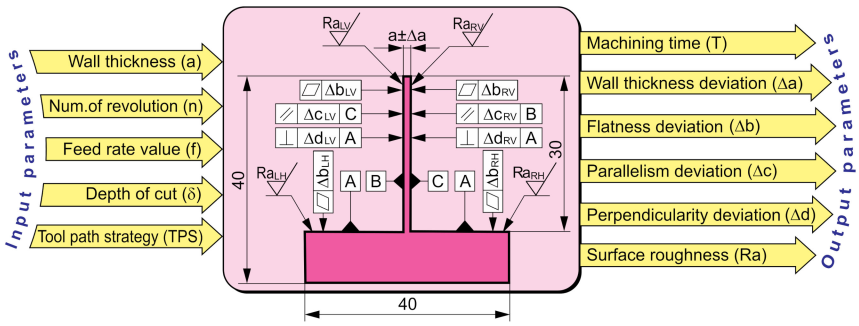


Figure 2. The optimization tasks (unit: mm).

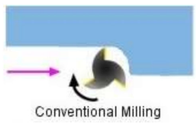
The main optimization task refers to determining the optimal machining parameters of the observed thin-walled parts as an objective function by achieving high productivity, the accuracy of measures, quality of machining, the accuracy of form and surface position order of importance of the criteria. The hierarchical structure of the optimization problem consists of the following elements:

- Objective function: Optimum machining parameter levels of the line-type thin-walled parts of aluminum alloy from the aspect of high productivity, accuracy, and quality of machining;
- Optimization criteria: Output parameters of the machining process (MRR, Δa, Δb, Δc, Δd, and Ra);
- Alternative solutions (alternative variants): Selected combinations-levels of input parameters of the process (a, n, f, δ, and TPS) based on the designed experimental plan.

3.2. Experimental Design

Assuming that the mathematical relations of the input parameters and performances of the process are complex and nonlinear, three levels of variations were chosen for each parameter (Table 1). When choosing the parameters' values, literature recommendations, technical and technological limitations of the machine and tools, characteristics of the workpiece material, and previous experimental research were taken into account.

Table 1. Input parameters and levels of variation.

Parameter	Unit	Level		
Wall thickness (a)	mm	0.5	1	1.5
Number of revolutions (n)	rpm	6000	12,000	24,000
Feed rate (f)	mm/min	600	1200	2400
Depth of cut (δ)	mm	1	2	3
Tool path strategy (TPS)—Cimatron	-	Path 1-climb 	Path 2-conventional 	Path 3-mixed 

The planning of the experiment was performed using the Taguchi methodology, which is very often and efficiently applied for experimental analysis and optimization of production processes [63]. Based on the selected varying input machining parameters and the corresponding levels of variation, an experimental design matrix was made using the standard Taguchi orthogonal array L_{27} consisting of 27 rows (experimental trials) and 13 columns (parameter levels) where the input parameter levels are connected to columns 1, 2, 5, 9 and 12.

3.3. Realizing the Experiments

A blank material used for machining sample parts is the prismatic shape (70 mm × 40 mm × 40 mm), and the material is alloy Al7075 (AlZnMgCu1.5). This aluminum alloy has very good mechanical properties, high fatigue, and corrosion resistance, making it suitable for the machining of thin-walled structures. The chemical composition of this alloy is: Al (87.1–91.4%), Cr (0.18–0.28%), Cu (1.2–2%), Fe (≤0.5%), Mg (2.1–2.9%), Mn (≤0.3%), Si (≤0.4%), Ti (≤0.2%), Zn (5.1–6.1%). The main mechanical properties are tensile strength (560 MPa), Rp0.2 (500 MPa), yield strength (7%), hardness (150 HBW). Experimental investigations were performed on the high-speed CNC vertical milling machining center DIGMA HSC 850 (Frezal, Ruma, Serbia), using high-pressure air as a coolant during machining. The Alu-power carbide end mill cutter, manufactured by YG (Incheon, South Korea), was used for machining parts. The basic tool information is the following: diameter D = 8 mm, helix angle 30°, 2 flutes, corner radius R = 0.6 mm, flute length L_1 = 10 mm, overall length L = 70 mm. Figure 3 shows the machining system used to realize the experimental machining process with the image of the machine tool's workspace, i.e., the main spindle with the tool and the workpiece clamped in the machine fixtures.

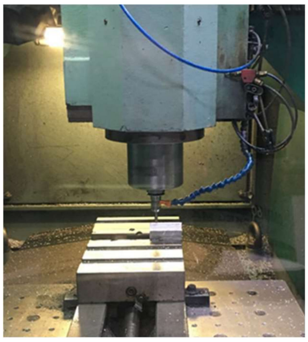


Figure 3. Workspace of the machine tool.

To avoid deformations in the machining process, analysis of the positive cases from the literature [9,28] and previous implementation of the experiments made it possible to choose a strategy of alternating machining of both sides of the wall. According to Figure 4, the case with the depth of cut of δ = 3 mm is represented.

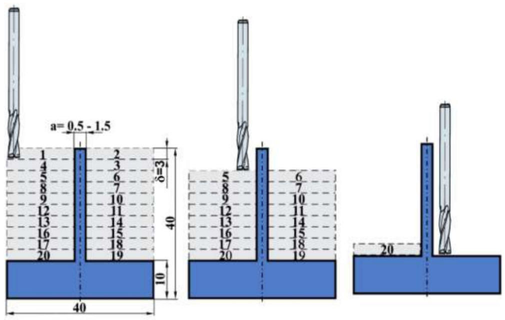


Figure 4. Selected machining passes sequence for the machining of thin-walled parts.

3.4. Measuring the Experimental Results

As stated in the research plan, the following machining parameters were measured: machining time—T (min), wall thickness deviation—Δa (mm), flatness deviation—Δb (mm), parallelism deviation—Δc (mm), perpendicularity deviation—Δd (mm) and surface roughness—Ra (μm), as shown in Figure 2.

Based on the measured machining time for different levels of alternative input parameters, the calculation of the material removal rate (MRR) was done. It is considered an optimization criterion that shows machining productivity according to Equation (4).

$$\mathrm{MRR} = \frac{\mathrm{V}}{\mathrm{T}} \left(\mathrm{mm}^3/\mathrm{min}\right) \tag{4}$$

where:

- V–the volume of removed material (mm^3);
- T–the machining time (min).

The measurement of the next four parameters (Δa, Δb, Δc, and Δd) was done using Coordinate Measuring Machines (CMM) Mitutoyo Strato—APEX 9166 Unimet, Kac, Serbia), Figure 5. Depending on the type of parameter (according to Figure 2), measurements were realized in certain places and surfaces, which is explained below for each parameter specifically. Then, the mean values of these measurements were calculated for each parameter, which represent the output values of these parameters.

Figure 5. Coordinate Measuring Machines (CMM) Mitutoyo Strato—APEX 9166.

The wall thickness (a) was measured in five places at equal distances along the length of the part, and then the mean deviation of the wall thickness (Δa) was calculated as the output parameter.

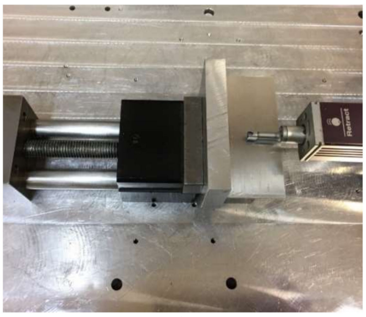
The flatness deviation (Δb) was measured for the left and the right side, as well as the horizontal and the vertical surface. Therefore, we have the following flatness deviations: Δb_{RV}—right vertical side of the wall, Δb_{RH}—right horizontal surface, Δb_{LV}—left vertical side of the wall, and Δb_{LH}—left horizontal side of the wall.

The parallelism deviation (Δc) was measured for the left and right side of the wall, i.e., Δc_{LV}—the parallelism deviation of the wall's left vertical side, Δc_{RV}—the parallelism deviation of the right vertical side of the wall. The perpendicularity deviation (Δd) was measured for the left and right side of the wall, so we have Δd_{LV}—the perpendicularity deviation of the left vertical side of the wall, Δd_{RV}—the perpendicularity deviation of the right vertical side of the wall.

Measurement of the surface roughness was performed using the Mitutoyo SJ-301 device (Unimet, Kac, Serbia), Figure 6. Roughness was measured perpendicularly to the direction of the tool movement. Since it is a linear part, it is divided into the left and right side, so that the roughness of the left side of the horizontal and the vertical surface Ra_{LH} and Ra_{LV}, as well as the right side Ra_{RH} and Ra_{RV} were measured. Experimental plan matrices with measurement results (T, Δa, Δb, Δc, Δd, Ra) and calculations (MRR) are shown in Table 2.

A more detailed analysis of the results showed that the input parameters have different effects on the characteristics of the output results-optimization criteria, implying the need to optimize the machining parameters for thin-walled parts using MCDM methodologies.

(**a**)



(**b**)

Figure 6. Measurement of the surface roughness (Ra) using Mitutoyo SJ-301 device: (**a**) Horizontal surfaces; (**b**) Vertical surfaces.

Table 2. Experimental design and the results of measurements/calculations.

No.	Input Parameters					Output Parameters—Optimization Criteria						
	a mm	n rpm	f mm/min	δ mm	TPS -	T hh:mm:ss	MRR mm^3/min	Δa mm	Δb mm	Δc mm	Δd mm	Ra µm
1	0.5	6000	600	1	1	00:36:40	2262.252	0.0420	0.03875	0.0690	0.0840	0.2500
2	0.5	6000	1200	2	2	00:11:30	7213.043	0.0240	0.12725	0.2415	0.3830	1.3100
3	0.5	6000	2400	3	3	00:19:29	4257.558	0.0260	0.04925	0.0845	0.1220	0.8300
4	0.5	12,000	600	2	3	00:21:06	3931.280	0.0160	0.04850	0.1035	0.1160	0.8425
5	0.5	12,000	1200	3	1	00:42:10	1967.178	0.0160	0.03475	0.0645	0.0925	0.3375
6	0.5	12,000	2400	1	2	00:09:16	8951.117	0.0220	0.06475	0.1085	0.1015	0.8600
7	0.5	24,000	600	3	2	00:47:16	1754.924	0.0120	0.04175	0.1160	0.1335	0.4100
8	0.5	24,000	1200	1	3	00:17:17	4799.514	0.0260	0.03375	0.0875	0.1195	0.3950
9	0.5	24,000	2400	2	1	00:08:37	9626.320	0.0380	0.03975	0.0685	0.1000	0.2925
10	1.0	6000	600	2	2	00:22:33	3631.929	0.0600	0.05750	0.1355	0.1250	1.5325
11	1.0	6000	1200	3	3	00:29:03	2819.277	0.0380	0.02525	0.1355	0.1730	0.5800
12	1.0	6000	2400	1	1	00:11:23	7194.940	0.0100	0.02050	0.1135	0.1170	0.5100
13	1.0	12,000	600	3	1	01:03:54	1281.690	0.0080	0.01150	0.0890	0.0940	0.1375
14	1.0	12,000	1200	1	2	00:17:46	4609.670	0.0560	0.02375	0.0600	0.1090	0.6325
15	1.0	12,000	2400	2	3	00:05:28	14,980.790	0.0260	0.03650	0.0905	0.1510	1.0050
16	1.0	24,000	600	1	3	00:28:03	2919.786	0.0420	0.01650	0.1305	0.1195	0.1850
17	1.0	24,000	1200	2	1	00:12:00	6825.000	0.0280	0.01550	0.0790	0.1405	0.1925
18	1.0	24,000	2400	3	2	00:23:00	3560.870	0.0360	0.02475	0.0960	0.1060	0.3050
19	1.5	6000	600	3	3	00:58:06	1391.566	0.0240	0.26175	0.0925	0.2325	0.2575
20	1.5	6000	1200	1	1	00:17:49	4537.801	0.0140	0.27300	0.2115	0.3290	0.3825
21	1.5	6000	2400	2	2	00:06:13	13,004.660	0.0660	0.31675	0.3165	0.4715	1.9800
22	1.5	12,000	600	1	2	00:31:23	2576.236	0.0400	0.28875	0.2180	0.3335	1.1600
23	1.5	12,000	1200	2	3	00:11:17	7165.647	0.0160	0.29850	0.2790	0.4590	1.3275
24	1.5	12,000	2400	3	1	00:21:59	3677.842	0.0100	0.27100	0.1790	0.2725	0.4075
25	1.5	24,000	600	2	1	00:21:33	3751.740	0.0100	0.27100	0.3480	0.3215	0.1500
26	1.5	24,000	1200	3	2	00:35:27	2280.677	0.0120	0.27875	0.2615	0.4245	0.2725
27	1.5	24,000	2400	1	3	00:08:18	9740,964	0.0120	0.27475	0.2100	0.3400	0.5050

4. Results and Discussion

4.1. Determining the Weight Coefficients of the Criteria

To determine the optimal machining parameters of the observed line-type thin-walled parts, it was necessary to define the optimization criteria correctly and then determine their weight coefficients. As a large amount of material is removed in the process of production of these parts, it is necessary to achieve high productivity and, at the same time, the best possible quality and accuracy of machining. For that purpose, the material removal rate (MRR) was chosen as the most important criterion, followed by the dimensional accuracy of the wall thickness (Δa) and the surface roughness (Ra). The corresponding hierarchical structure—pairwise comparison matrix (each criterion is compared with every other)—is presented using the following decision matrix in Table 3.

Table 3. Hierarchical structure of the pairwise criteria comparison.

Parameters	MRR	Δa	Δb	Δc	Δd	Ra
MRR	1	3	5	5	5	3
Δa	-	1	2	2	2	1
Δb	-	-	1	1	1	1/2
Δc	-	-	-	1	1	1/2
Δd	-	-	-	-	1	1/2
Ra	-	-	-	-	-	1

The approximation AHP method [44] consisted of four steps, was used to determine the weight coefficients—normalized eigenvectors of the criteria. The first step refers to the definition of the processed matrix—a table of comparison of all criteria where the values below the diagonal of the matrix get inverted values above the diagonal. The second step is to determine the sum of all the column elements in the table. The results of the first two steps are shown in Table 4.

Table 4. Steps 1 and 2 of the approximation Analytic Hierarchy Process (AHP) methodology for determining weight coefficients.

Parameters	MRR	Δa	Δb	Δc	Δd	Ra
MRR	1.0000	3.0000	5.0000	5.0000	5.0000	3.0000
Δa	0.3333	1.0000	2.0000	2.0000	2.0000	1.0000
Δb	0.2000	0.5000	1.0000	1.0000	1.0000	0.5000
Δc	0.2000	0.5000	1.0000	1.0000	1.0000	0.5000
Δd	0.2000	0.5000	1.0000	1.0000	1.0000	0.5000
Ra	0.3333	1.0000	2.0000	2.0000	2.0000	1.0000
Sum	2.2667	6.5000	12.0000	12.0000	12.0000	6.5000

In the third step, each column's elements are divided by the sum of the values of that column, which was obtained in the previous step. In the fourth step, each row's sum is determined, followed by the mean value of that row. The column consisting of these mean values represents the normalized eigenvector of the criterion (column W_j), i.e., the weight coefficients of the criterion W_j. The results of the third and fourth steps are given in Table 5, and the calculated values of weight coefficients are as follows: $W_{MRR} = 0.43571$, $W_{\Delta a} = 0.15913$, $W_{Ra} = 0.15913$, $W_{\Delta b} = 0.08201$, $W_{\Delta c} = 0.08201$, $W_{\Delta d} = 0.08201$ and the sum of these values $\Sigma W_i = 1.00$.

Table 5. Steps 3 and 4 of the approximation Analytic Hierarchy Process (AHP) methodology for determining weight coefficients.

Parameters	MRR	Δa	Δb	Δc	Δd	Ra	Sum	W_j	λ_i
MRR	0.4412	0.4615	0.4167	0.4167	0.4167	0.4615	2.6143	0.43571	6.0147
Δa	0.1471	0.1538	0.1667	0.1667	0.1667	0.1538	0.9548	0.15913	6.0051
Δb	0.0882	0.0769	0.0833	0.0833	0.0833	0.0769	0.4921	0.08201	6.0028
Δc	0.0882	0.0769	0.0833	0.0833	0.0833	0.0769	0.4921	0.08201	6.0028
Δd	0.0882	0.0769	0.0833	0.0833	0.0833	0.0769	0.4921	0.08201	6.0028
Ra	0.1471	0.1538	0.1667	0.1667	0.1667	0.1538	0.9548	0.15913	6.0051
-	-	-	-	-	-		-	$\Sigma = 1.0000$	$\lambda_{max} = 6.0147$

To determine the decision-maker's consistency, the one who defines the level of errors when comparing the criteria, the calculation of the consistency ratio was performed. The consistency index CI according to Equation (5), is defined first, followed by the consistency ratio CR according to Equation (6), where the random index RI = 1.24 is adopted based on the number of criteria in the model (n = 6) [44].

$$CI = \frac{\lambda max - n}{n - 1} = \frac{6.0147 - 6}{6 - 1} = 0.0029 \quad (5)$$

$$CR = \frac{CI}{RI} = \frac{0.0029}{1.24} = 0.0024 \quad (6)$$

The value of the consistency ratio equals CR = 0.0024 ≤ 0.1, which means that the decision-makers error when estimating the comparison of the criteria is very small, based on which we can conclude that the comparison of the criteria was performed adequately.

4.2. Applying the MCDM Methods

4.2.1. Results of Applying MCDM Methods

Table 6 shows the resulting coefficients obtained by applying 14 MCDM methods based on which the ranking of alternative levels of the machining parameters for milling of thin-walled parts was performed. The designations and names of these coefficients for all applied MCDM methods are given below: GRA (GRG—gray relational grade), AHP (F_i—composite normalized vector), MOORA (Y_i—normalized assessment value of alternatives, TOPSIS (CCo—relative closeness to the "ideal" solution), ROV (U_i—mean value of the utility function of alternatives), COPRAS (U_j%—degree of utility alternatives), ARAS (U_i%—degree of utility alternatives), WASPAS (Q_j—overall relative importance of the alternative), VIKOR (Q_i—minimum distance from "ideal" solutions), OCRA (P_i—overall performance rating), EDAS (S_i—values of appraisal scores), MABAC (S_i—values of criteria function of alternatives), SAW (S_i—overall ranking index of *i*-th alternative) and SPW (S_i—overall ranking index of *i*-th alternative).

4.2.2. Integrative Multi-Criteria Ranking of the Alternative Levels of Machining Parameters

Based on the results from Table 6, which refer to the individual evaluation and ranking of alternative levels of high-speed machining process parameters based on fourteen different MCDM methods, a comprehensive comparison and ranking of twenty-seven levels of parameters according to the experiment plan was performed using the integrated assessment methodology. To obtain a comprehensive final ranking of the machining parameter levels based on the results of applying the MCDM methods, the agreement of the obtained values of the correlation ratios with the set limit values was tested.

Table 7 provides an overview of the ranks of alternative levels, values of standard deviation by levels (σ_i), while the lower part of the table gives the following values: maximum standard deviation (σ_{max}), average standard deviation (σ_{av}), Kendall's rank correlation coefficient (W), and the average Spearman rank correlation coefficient (R). Table 8 shows the values of Spearman's correlation coefficients of the ranks of alternative parameter levels of all applied MCDM methods by pairs.

After the first iteration, it was stated that the results obtained by applying these 14 MCDM methods could not be used for integrative ranking of the alternative parameter levels because the limit values of the first given criterion are not met ($0.9 \leq R_i \leq 1$), i.e., there are several combinations of methods where Spearman's rank correlation coefficient R_i is less than the limit value of 0.9.

Since the set criteria were not met within the first iteration, it was necessary to approach the second iteration, which is presented below with the corresponding results.

Second Iteration

After analyzing the results in Table 8, it was concluded that there is a group of MCDM methods that meet all the criteria which are proven through the introduction of the second iteration. The second iteration includes the integrated application of the following five methods: MOORA, ROV, EDAS, MABAC, and SPW.

The results of comparing the ranks of the alternative levels of parameters are given in Table 9, and the values of Spearman's rank correlation coefficients are presented in Table 10.

Table 6. Resulting coefficients of applying multi-criteria decision making (MCDM) methods and the rank of the alternative levels.

No. Exp.	MCDM Method																											
	GRA		AHP		MOORA		TOPSIS		ROV		COPRAS		ARAS		WASPAS		VIKOR		OCRA		EDAS		MABAC		SAW		SPW	
	GRG	Rank	F_i	Rank	Y_i	Rank	CCo	Rank	U_i	Rank	U_j%	Rank	U_i%	Rank	Q_j	Rank	Q_i	Rank	P_i	Rank	S_i	Rank	S_i	Rank	S_i	Rank	S_i	Rank
1	0.5764	3	0.0323	16	−0.0360	17	0.3293	23	0.2413	16	0.4786	19	51.1608	16	0.3178	16	0.7653	22	3.9233	12	0.4453	16	−0.0052	16	0.3613	15	0.2742	19
2	0.2316	25	0.0323	17	−0.0374	19	0.4472	8	0.2309	19	0.5260	14	51.1481	17	0.3006	21	0.5648	8	2.4153	22	0.4340	18	−0.0261	19	0.3253	22	0.2759	18
3	0.3898	16	0.0306	21	−0.0212	12	0.3603	16	0.2623	12	0.5123	15	48.4040	21	0.3171	17	0.6418	11	3.6446	14	0.4940	12	0.0368	12	0.3330	19	0.3013	14
4	0.4056	14	0.0317	19	−0.0176	10	0.3617	15	0.2683	10	0.5299	13	50.1936	19	0.3282	15	0.6459	12	3.7772	13	0.5046	10	0.0488	10	0.3463	16	0.3101	13
5	0.5987	2	0.0337	14	−0.0178	11	0.3465	19	0.2688	9	0.6426	9	53.2646	14	0.3341	14	0.7317	18	4.3339	6	0.5044	11	0.0497	9	0.3795	12	0.2887	15
6	0.4126	13	0.0451	8	0.0420	4	0.5925	5	0.3378	4	0.7384	6	71.2942	8	0.4425	6	0.3067	3	4.0542	11	0.7056	4	0.1878	4	0.4714	7	0.4136	5
7	0.4446	12	0.0297	22	−0.0277	13	0.3374	21	0.2551	13	0.5564	11	46.9321	22	0.2905	22	0.7642	21	4.1475	9	0.4707	13	0.0225	13	0.3271	21	0.2540	21
8	0.4508	11	0.0364	11	0.0044	7	0.4126	10	0.2916	7	0.6372	10	57.4954	11	0.3769	8	0.5681	9	4.3114	7	0.5841	7	0.0954	7	0.3858	11	0.3680	7
9	0.5478	5	0.0532	3	0.0638	2	0.6424	2	0.3603	2	0.8387	3	84.1570	3	0.5277	2	0.2387	2	4,7149	5	0.7832	2	0.2328	2	0.5527	3	0.5028	3
10	0.2827	23	0.0230	26	−0.0958	26	0.2392	26	0.1667	26	0.3419	26	36.3544	26	0.2303	25	0.8316	24	1.9776	24	0.2374	26	−0.1544	26	0.2490	26	0.2116	25
11	0.3517	17	0.0257	24	−0.0483	21	0.3112	25	0.2243	20	0.4200	23	40.6486	24	0.2572	23	0.7696	23	3.6094	15	0.4058	21	−0.0392	20	0.2667	24	0.2478	23
12	0.5381	6	0.0510	5	0.0465	3	0.5317	6	0.3450	3	0.8320	4	80.6140	5	0.5145	4	0.3718	5	4.8477	2	0.7245	3	0.2023	3	0.5277	5	0.5013	4
13	0.7522	1	0.0539	2	−0.0115	8	0.3569	18	0.2770	8	0.9177	2	85.2771	2	0.4474	5	0.7480	20	4.7919	3	0.5257	8	0.0661	8	0.5661	2	0.3286	9
14	0.5216	7	0.0351	12	-0.0325	15	0.3594	17	0.2436	15	0.4814	18	55.4603	12	0.3470	12	0.6580	13	3.5684	16	0.4596	15	−0.0007	15	0.3763	13	0.3176	11
15	0.4750	10	0.0632	1	0.1144	1	0.8358	1	0.4231	1	1.0000	1	100.000	1	0.5693	1	0.0000	1	4.7259	4	0.9478	1	0.3583	1	0.6323	1	0.5063	1
16	0.4937	8	0.0379	10	−0.0306	14	0.3464	20	0.2450	14	0.4957	17	59.9038	10	0.3520	10	0.7300	17	4.1193	10	0.4668	14	0.0023	14	0.3860	10	0.3180	10
17	0.5595	4	0.0525	4	0.0385	5	0.5125	7	0.3313	5	0.7951	5	82.9977	4	0.5170	3	0.4115	6	4.8665	1	0.7010	5	0.1747	5	0.5298	4	0.5043	2
18	0.4781	9	0.0345	13	−0.0175	9	0.3639	14	0.2635	11	0.5478	12	54.5216	13	0.3469	13	0.6704	14	4.1701	8	0.5100	9	0.0392	11	0.3650	14	0.3287	8
19	0.3448	19	0.0239	25	−0.0634	24	0.3122	24	0.2028	23	0.3526	24	37.7680	25	0.2251	26	0.8691	26	2.4285	21	0.3402	24	−0.0822	23	0.2649	25	0.1854	26
20	0.3086	22	0.0314	20	−0.0348	16	0.3917	11	0.2325	18	0.4646	20	49.6901	20	0.3075	19	0.6800	15	2.5104	20	0.4390	17	−0.0228	18	0.3278	20	0.2873	16
21	0.2103	26	0.0456	7	−0.0576	23	0.5986	4	0.1909	24	0.7290	7	72.0641	7	0.3477	11	0.5108	7	0.0000	27	0.3489	23	−0.1060	24	0.4417	8	0.2537	22
22	0.1829	27	0.0161	27	−0.1191	27	0.2094	27	0.1285	27	0.2783	27	25.4879	27	0.1650	27	0.9429	27	0.7382	26	0.1485	27	−0.2307	27	0.1721	27	0.1579	27
23	0.2370	24	0.0336	15	−0.0556	22	0.4410	9	0.2039	22	0.5006	16	53.0725	15	0.3031	20	0.6126	10	1.2713	25	0.3616	22	−0.0799	22	0.3403	18	0.2659	20
24	0.3477	18	0.0322	18	−0.0365	18	0.3693	13	0.2341	17	0.4494	21	50.9218	18	0.3131	18	0.7152	16	2.5758	19	0.4316	19	−0.0196	17	0.3442	17	0.2821	17
25	0.4016	15	0.0407	9	−0.0445	20	0.3823	12	0.2171	21	0.4311	22	64.2962	9	0.3665	9	0.7407	19	2.6001	18	0.4070	20	−0.0535	21	0.4213	9	0.3116	12
26	0.3297	21	0.0275	23	−0.0703	25	0.3310	22	0.1861	25	0.3444	25	43.4779	23	0.2562	24	0.8583	25	2.2118	23	0.3170	25	−0.1156	25	0.2911	23	0.2212	24
27	0.3345	20	0.0474	6	0.0313	6	0.6367	3	0.3115	6	0.7059	8	74.9848	6	0.4359	7	0.3165	4	2.9813	17	0.6602	6	0.1352	6	0.4798	6	0.3919	6

Table 7. Results of comparing the ranks of the alternative parameter levels of the applied MCDM methods.

No. Exp.	GRA	AHP	MOORA	TOPSIS	ROV	COPRAS	ARAS	WASPAS	VIKOR	OCRA	EDAS	MABAC	SAW	SPW	Average Value of Ranks	Final Rank of Alternative	σ_i—Stand Deviation
1	3	16	17	23	16	19	16	16	22	12	16	16	15	19	16.33	15	4.721
2	25	17	19	8	19	14	17	21	8	22	18	19	22	18	16.83	17	4.877
3	16	21	12	16	12	15	21	17	11	14	12	12	19	14	14.06	14	3.371
4	14	19	10	15	10	13	19	15	12	13	10	10	16	13	12.67	11	3.082
5	2	14	11	19	9	9	14	14	18	6	11	9	12	15	12.00	10	4.551
6	13	8	4	5	4	6	8	6	3	11	4	4	7	5	5.67	5	2.894
7	12	22	13	21	13	11	22	22	21	9	13	13	21	21	16.67	16	5.014
8	11	11	7	10	7	10	11	8	9	7	7	7	11	7	8.39	7	1.805
9	5	3	2	2	2	3	3	2	2	5	2	2	3	3	2.61	2	1.051
10	23	26	26	26	26	26	26	25	24	24	26	26	26	25	24.94	26	1.008
11	17	24	21	25	20	23	24	23	23	15	21	20	24	23	20.89	23	2.872
12	6	5	3	6	3	4	5	4	5	2	3	3	5	4	4.00	3	1.231
13	1	2	8	18	8	2	2	5	20	3	8	8	2	9	8.72	8	5.908
14	7	12	15	17	15	18	12	12	13	16	15	15	13	11	13.61	13	2.818
15	10	1	1	1	1	1	1	1	1	4	1	1	1	1	1.67	1	2.476
16	8	10	14	20	14	17	10	10	17	10	14	14	10	10	13.06	12	3.539
17	4	4	5	7	5	5	4	3	6	1	5	5	4	2	4.44	4	1.541
18	9	13	9	14	11	12	13	13	14	8	9	11	14	8	11.17	9	2.301
19	19	25	24	24	23	24	25	26	26	21	24	23	25	26	23.83	25	1.979
20	22	20	16	11	18	20	20	19	15	20	17	18	20	16	17.50	20	2.828
21	26	7	23	4	24	7	7	11	7	27	23	24	8	22	17.72	21	8.939
22	27	27	27	27	27	27	27	27	27	26	27	27	27	27	26.61	27	0.267
23	24	15	22	9	22	16	15	20	10	25	22	22	18	20	19.00	22	4.957
24	18	18	18	13	17	21	18	18	16	19	19	17	17	17	17.17	18	1.785
25	15	9	20	12	21	22	9	9	19	18	20	21	9	12	17.17	18	5.229
26	21	23	25	22	25	25	23	24	25	23	25	25	23	24	23.78	24	1.311
27	20	6	6	3	6	8	6	7	4	17	6	6	6	6	7.28	6	4.781
																Maximum standard deviation σ_{max} =	8.939
																Average standard deviation σ_{av} =	3.227
																Kendall's rank correlation coefficient W =	0.786
																Average Spearman rank correlation coefficient R =	0.770

Table 8. Spearman's rank correlation coefficients of the applied MCDM methods.

Methods	GRA	AHP	MOORA	TOPSIS	ROV	COPRAS	ARAS	WASPAS	VIKOR	OCRA	EDAS	MABAC	SAW	SPW
GRA	1	0.5543	0.6862	0.0739	0.7118	0.5427	0.5543	0.6343	0.1752	0.8993	0.6935	0.7118	0.6245	0.6368
AHP	-	1	0.7473	0.7643	0.7295	0.8419	**1.0000**	**0.9634**	0.7375	0.6148	0.7503	0.7295	**0.9823**	0.8529
MOORA	-	-	1	0.6361	**0.9945**	0.8590	0.7473	0.8492	0.7320	0.8669	**0.9988**	**0.9945**	0.7961	**0.9316**
TOPSIS	-	-	-	1	0.6013	0.7320	0.7643	0.7369	**0.9457**	0.2784	0.6319	0.6013	0.7186	0.7131
ROV	-	-	-	-	1	0.8516	0.7295	0.8327	0.7082	0.8803	**0.9945**	**1.0000**	0.7839	**0.9115**
COPRAS	-	-	-	-	-	1	0.8419	0.8370	0.7778	0.7167	0.8639	0.8516	0.8486	0.7808
ARAS	-	-	-	-	-	-	1	**0.9634**	0.7375	0.6148	0.7503	0.7295	**0.9823**	0.8529
WASPAS	-	-	-	-	-	-	-	1	0.7527	0.7204	0.8492	0.8327	**0.9829**	**0.9328**
VIKOR	-	-	-	-	-	-	-	-	1	0.3834	0.7326	0.7082	0.7057	0.7723
OCRA	-	-	-	-	-	-	-	-	-	1	0.8700	0.8803	0.6795	0.7790
EDAS	-	-	-	-	-	-	-	-	-	-	1	**0.9945**	0.7961	**0.9292**
MABAC	-	-	-	-	-	-	-	-	-	-	-	1	0.7839	**0.9115**
SAW	-	-	-	-	-	-	-	-	-	-	-	-	1	0.8724
SPW	-	-	-	-	-	-	-	-	-	-	-	-	-	1

Table 9. Results of comparing the ranks of the alternative parameter levels—the second iteration.

No. Exp.	MOORA	ROV	EDAS	MABAC	SPW	Average Value of Ranks	Final Rank of the Alternative	σ—Stand. Deviation
1	17	16	16	16	19	16.80	16	1.3038
2	19	19	18	19	18	18.60	19	0.5477
3	12	12	12	12	14	12.40	12	0.8944
4	10	10	10	10	13	10.60	10	1.3416
5	11	9	11	9	15	11.00	11	2.4495
6	4	4	4	4	5	4.20	4	0.4472
7	13	13	13	13	21	14.60	15	3.5777
8	7	7	7	7	7	7.00	7	0.0000
9	2	2	2	2	3	2.20	2	0.4472
10	26	26	26	26	25	25.80	26	0.4472
11	21	20	21	20	23	21.00	21	1.2247
12	3	3	3	3	4	3.20	3	0.4472
13	8	8	8	8	9	8.20	8	0.4472
14	15	15	15	15	11	14.20	14	1.7889
15	1	1	1	1	1	1.00	1	0.0000
16	14	14	14	14	10	13.20	13	1.7889
17	5	5	5	5	2	4.40	5	1.3416
18	9	11	9	11	8	9.60	9	1.3416
19	24	23	24	23	26	24.00	24	1.2247
20	16	18	17	18	16	17.00	17	1.0000
21	23	24	23	24	22	23.20	23	0.8367
22	27	27	27	27	27	27.00	27	0.0000
23	22	22	22	22	20	21.60	22	0.8944
24	18	17	19	17	17	17.60	18	0.8944
25	20	21	20	21	12	18.80	20	3.8341
26	25	25	25	25	24	24.80	25	0.4472
27	6	6	6	6	6	6.00	6	0.0000
							Maximum standard deviation σ_{max} =	3.8341
							Average standard deviation σ_{av} =	1.0729
							Kendall's rank correlation coefficient W =	0.9728
							Average Spearman rank correlation coefficient R =	0.9708

Table 10. Spearman's rank correlation coefficients—the second iteration.

Methods	MOORA	ROV	EDAS	MABAC	SPW
MOORA	1	0.9945	0.9988	0.9945	0.9316
ROV	-	1	0.9945	1.0000	0.9115
EDAS	-	-	1	0.9945	0.9292
MABAC	-	-	-	1	0.9115
SPW	-	-	-	-	1

Based on the obtained results shown in Tables 9 and 10, it can be concluded that for the combination of the MCDM methods MOORA, ROV, EDAS, MABAC, and SPW:

1. The first criterion is met—the Spearman's rank correlation coefficient is for all combinations of methods within the limit value $0.9 \le R_i \le 1$ ($R_{min} = 0.9115$),
2. The second criterion is met—Kendall's rank correlation coefficient is in the range of $0.9 \le W$ ($W = 0.9728$),
3. The third criterion is met—average Spearman rank correlation coefficient is in the range of $0.9 \le R$ ($R = 0.9708$) and
4. The fourth criterion is met—the average standard deviation is within the limit value $\sigma_{av} \le 1.5$ ($\sigma_{av} = 1.0729$)

Since all the correlation criteria for the integrative application of MCDM methods are met, the optimal rank of the alternative levels of process parameters is given in Table 9. Table 11 shows the five best-ranked levels with values of machining parameters (a, n, f, δ, and TPS) and the values of the obtained optimization criteria (MRR, Δa, Δb, Δc, Δd, and Ra). Figure 7 presents the ranking chart of the top 5 alternative experiments according to the selected MCDM methods.

Table 11. The optimal alternative levels of the high-speed process parameters for line-type thin-walled parts.

No Exp.	a	n	f	δ	TPS	MRR	Δa	Δb	Δc	Δd	Ra	Rank
	mm	rpm	mm/min	mm	-	mm^3/min	mm	mm	mm	mm	μm	
15	1.0	12,000	2400	2	3	14,980.790	0.0260	0.03650	0.0905	0.1510	1.0050	1
9	0.5	24,000	2400	2	1	9626.320	0.0380	0.03975	0.0685	0.1000	0.2925	2
12	1.0	6000	2400	1	1	7194.940	0.0100	0.02050	0.1135	0.1170	0.5100	3
6	0.5	12,000	2400	1	2	8951.117	0.0220	0.06475	0.1085	0.1015	0.8600	4
17	1.0	24,000	1200	2	1	6825.000	0.0280	0.01550	0.0790	0.1405	0.1925	5

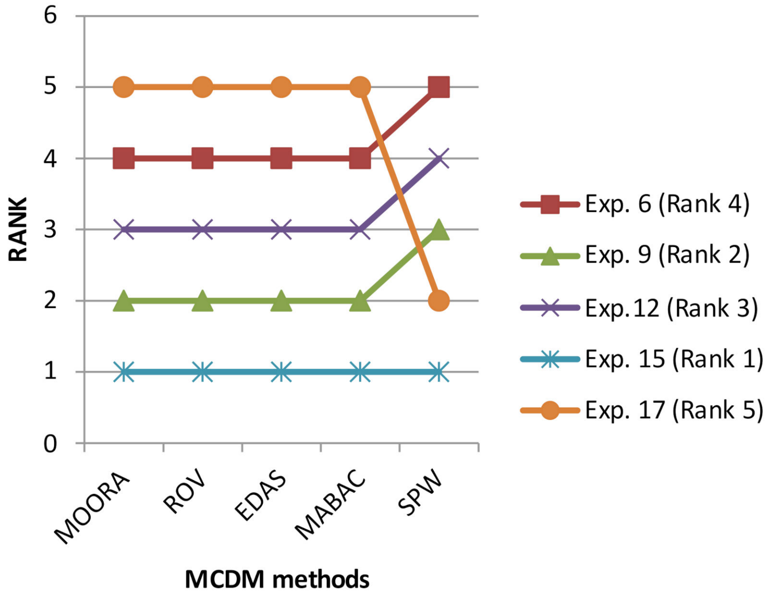


Figure 7. Ranking chart of the 5 best alternative experiments for the selected MCDM methods.

5. Conclusions

In this study, the machining parameters for milling of line-type thin-walled parts made of aluminum alloy Al 7075 were analyzed. The influence of wall thickness (a), number of revolutions (n), feed rate (f), depth of cut (δ), and tool path strategy (TPS) was examined on machining time (T)/material removal rate (MRR), wall thickness deviation (Δa), surface flatness deviation (Δb), surface parallelism deviation (Δc), surface perpendicularity deviation (Δd) and surface roughness (Ra), all of them representing the optimization criteria.

Considering the characteristics of the process of high-speed milling of thin-walled parts, a comparison of optimization criteria using the AHP method was made, where the highest weight coefficient was obtained by the material removal rate (MRR), as a productivity opponent $W_{MRR} = 0.43571$, then weight coefficients of the wall thickness accuracy and surface roughness $W_{\Delta a} = 0.15913$, $W_{Ra} = 0.15913$, and finally the accuracy of form and accuracy of surface position $W_{\Delta b} = 0.08201$, $W_{\Delta c} = 0.08201$ and $W_{\Delta d} = 0.08201$. Twenty-seven experiments were conducted using the standard Taguchi orthogonal sequence L_{27}, and multi-criteria optimization was performed using 14 MCDM methods (GRA, AHP, MOORA, TOPSIS, ROV, COPRAS, ARAS, WASPAS, VIKOR, OCRA, EDAS, MABAC, SAW and SPW) According to this, the optimal alternative levels of input parameters for the defined objective function and their ranking were obtained.

Afterward, the obtained results were compared using correlation analysis based on Spearman's and Kendall's rank correlation coefficients and the standard deviation of the ranks of the alternative levels. At the output, the integrative decision on selecting the optimal level of high-speed machining parameters based on 5 MCDM methods (MOORA, ROV, EDAS, MABAC and SPW) that met the limits of correlation coefficients was made. The optimum machining parameter level is experiment No.15 with the following varying input parameters a = 1 mm, n = 12,000 rpm, f = 2400 mm/min, δ = 2 mm, TPS 3 and the output machining parameters as the optimization criteria: MRR=14,980.790 mm^3/min, Δa = 0.0260 mm, Δb = 0.03650 mm, Δc = 0.0905 mm, Δd = 0.1510 mm and Ra = 1.0050 µm.

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