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A Grey Fuzzy Approach to the Selection of Cutting Process from the Aspect of Technological Parameters

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Abstract: This study deals with the selection of the cutting process using the grey fuzzy relation approach. The analysis was performed using plasma arc machining, laser beam machining, and abrasive waterjet machining on three different workpiece thicknesses with different cutting speeds. The objective was to select the best cutting process considering several performance characteristics such as machining time, dimensional accuracy, kerf width, and surface roughness. Data normalization, grey relation coefficients, fuzzy inference system, and grey fuzzy relation grade are used to evaluate the machining performances of the machining processes. The developed fuzzy model can be used to study the effects of different cutting processes on technological features. The results show that the grey fuzzy technique can be effectively used for the analysis and selection of cutting processes.

Keywords: fuzzy logic; grey relational analysis; selecting machine tool; machining time; dimensional accuracy; surface quality

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1. Introduction

Today, non-conventional methods are increasingly used in the processing of sheet materials. Increasing the quality and precision of these machining systems reduces the need for multiple rework operations while achieving satisfactory accuracy, productivity, and economy [1]. The selection of the appropriate cutting process is an important activity from the point of view of investment efficiency in the development of the product or process [2]. From the aspect of machining performances such as surface quality, machining time—productivity and accuracy, the selection of suitable machine tools is the real challenge of today's production [3].

Among non-conventional machining methods, plasma arc machining (PAM), laser beam machining (LBM), and abrasive waterjet machining (AWJM) are most commonly used to cut steel sheets of various thicknesses [4]. Each of these methods has its advantages and disadvantages in terms of machining quality, dimensional accuracy, machining time, and more. For example, the main advantages of PAM are the efficient speed of material removal and the ability to cut different thicknesses, even up to 150 mm. It can be concluded that the productivity of this process is at a high level. In practice, PAM is considered a rough machining process due to the high concentration of energy on a small area [5]. This leads to irregular cut edges and a high value for kerf width, which ultimately results in a poor surface finish and low dimensional accuracy. Compared with the general plasma method, LBM has some obvious advantages. For example, when cutting thin steel sheets, LBM has a much higher cutting speed than plasma [6]. Dimensional accuracy is also better because the laser produces a much smaller width of cut on the workpiece [7]. However, the laser also has disadvantages. The main ones are the high cost of the equipment and the poor surface quality when cutting thicker steel sheets [8]. The aforementioned machining is mainly based on the thermal effect, i.e., the material removal from the workpiece is achieved by melting. This high heat has a negative effect on the integrity of the workpiece surface. On the other hand, AWJM is a cold process. Therefore, it is irreplaceable when a machined surface without thermal influence is required [9]. Compared to the previous two processes (PAM and LBM), the cutting speed of AWJM is relatively low, especially when cutting thicker materials. In general, it is quite difficult to make a decision on which process is best in terms of accuracy, surface quality and productivity. In these cases, decision support systems are used to make the right choice.

Poor decision making in cutting process selection can lead to serious problems in production. The process of selecting the machine for the specific operation in question is an important issue for any manufacturing company [10]. This is because irregular selection of cutting process can have a negative impact on technological parameters [11]. In general, these problems can have a negative impact on the overall effect of a production system. Technological parameters directly depend on the type of cutting process selected. However, making the right choice is a difficult process that requires a certain level of expertise and experience. To make a correct decision, a large amount of data must be analyzed, especially as many input/output factors as possible [12].

Selecting a cutting process is usually a difficult decision for engineers because there are many qualitative and quantitative characteristics that must be considered when selecting a suitable cutting process. To solve problems in this field, researchers have often used various methods based on multiple criteria, such as Analytic Hierarchy Process (AHP) [13], Multi criterion optimization and compromise solution (VIKOR) [14], Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) [15], Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [16], and Analytical Network Process (ANP) [17].

In addition to optimization-based approaches, models based on machine tool selection criteria are also widely used. Effective machine tool selection must compromise, therefore, between conflicting tangible and intangible factors. To address this, multi-criteria decision making (MCDM) has proven useful. Wu et al. developed a multi-criteria group decision procedure based on the fuzzy VIKOR method to solve a machine tool selection problem [18]. They used six main criteria (spindle speed, bar capacity, horsepower, capital cost, flexibility, and turning meter) that can affect the ability of CNC machines to perform the required production operations. The selection of the best machine tool from the increasing number of alternatives available on the market is a multi-criteria decision-making problem in the presence of many quantitative and qualitative characteristics. The selection of the best machine tool from the increasing number of alternatives existing in the market was explored by Ayağ and Oezdemir [19]. They applied an intelligent approach by merging both techniques—fuzzy logic and AHP—to evaluate the procurement cost of each alternative. Li et al. proposed a machine tool selection method based on a hybrid multi-criteria decision model [20]. They combined two techniques, fuzzy logic and VIKOR method, and pointed out that the best and worst selected machine tools have high agreement with the actual ranking in the real factory. Hafezalkotobs developed the VIKOR method based on interval target values of attributes and an interval decision matrix, and presented a novel normalization technique using the interval distance of interval number [21]. Then, they used interval distance as an improved formula compared to the interval distance equation available in the literature. Fahran et al. developed a model based on an analytical hierarchy process to support the selection of appropriate machine configurations for special purpose machines from the available alternatives [22]. They obtained different scenarios from the evaluation process of the developed model and showed the influence of changing the relevant importance of the elements in the hierarchy on the selection of special purpose machine configurations. Aghdaie et al. [23] proposed to combine decision making in machine tool selection with a combination of stepwise weight evaluation ratio analysis

(SWARA) and proportional evaluation of alternatives with grey relationships (COPRAS -G). Perhin and Min combined Fuzzy Linear Regression and Quality Function Deployment Zero-One Goal Programming to obtain the decision results of machine tool selection [24]. The first part of their research refers to the determination of the weight of each criterion by SWARA and the evaluation of alternatives by COPRAS -G to obtain a ranked list of machines. Previous research has been based mainly on the use of MCDM techniques in selecting similar machine tools based on cost and machine performance. On the other hand, very little research has addressed the development of decision-making systems that incorporate different machine tools performing the same operation.

Decision making in the analysis of different cutting methods requires a lot of information from the point of view of technological parameters. For example, Sengul [25] developed a fuzzy AHP method for choosing between plasma and laser cutting, in which the decision criteria are determined based on expert opinions. In his comparison, laser cutting technology was more important than plasma cutting. Khan and Maity used the TOPSIS method for simultaneous optimization of seven different non-conventional machining processes [26]. Similarly, Temucin and others conducted a study providing different system approaches in fuzzy environments for solving the problem of selecting the appropriate type of machining process using a fuzzy-based decision model [27]. They proposed a support model for deciding the potential application of seven processes: Laser, Plasma, Waterjet, Abrasive Waterjet, Electrochemical Machining, Electrical Discharge Machining, and Wire Discharge Machining when cutting carbon structural steel with a plate width of 10 mm. Kumari and Acherjee solved the problem of selecting nonconventional machining processes by using the importance of criteria through the correlation between criteria and the combined distance-based evaluation of multi-criteria decision methods. By combining the two methods, they successfully created a decision support model for eight different processes [28]. Productivity, shape property, workpiece type, accuracy and surface roughness, power consumption, and cost were used as criteria for evaluating the processes.

There are some techniques developed in the literature to solve MCDM problems. Mainly, AHP, VIKOR, TOPSIS, etc., are used, which are classical methods for solving multi-criteria problems. To improve the classical methods, they are often combined with artificial intelligence tools [29,30]. The combination of the above approaches is called hybrid MCDM technique. However, when many articles talk about hybrid techniques, little emphasis is placed on explaining the use of artificial intelligence methods. Fuzzy set theory has been proposed by many researchers to solve imprecise and indeterminate problems. However, it is not yet clear to what extent fuzzy logic and grey relational analysis can be applied. The use of fuzzy sets is not only due to the indeterminacy of judgments, but also due to the hesitation of experts on which decisions to make. Although it is still controversial to what extent fuzzy sets with grey relational analysis solve the problem of uncertainty, it is a simple and useful method that is widely used. Therefore, this article provides guidelines for selecting appropriate techniques for building fuzzy models in terms of representing fuzzification, aggregation, and defuzzification. In any grey fuzzy approach (GFA), it is crucial to establish an appropriate rule base that covers a wide range of possible solutions depending on the input criteria, as shown in this article.

Independently applied grey analysis characterizes the observed system as partially known or partially unknown. This kind of system with very little data can be used until a solution is created. Due to the small amount of data, there is a chance that the system based on grey relational analysis cannot fully present the final solution. In order to avoid these shortcomings, grey analysis is combined with the fuzzy logic method. The advantage of this method is designing a simple model that essentially replaces the mathematically based grey relational analysis. However, the model based on fuzzy logic largely depends on the acquired knowledge base. The integrated grey analysis and fuzzy logic technique has been successfully applied to solving many complicated problems such as the selection cutting process [31,32]. In applying this approach, the final solution is achieved in several steps. The first step is normalization, which serves as data preparation for grey relational analysis. The next step is the evaluation of the grey relational coefficient, depending on the established criteria: 'low is better' or 'high is better' [33]. In order to avoid some degree of uncertainty, fuzzy logic is used in the next step. In this process, the previously determined GRC values are fuzzified using membership functions. There are several types of membership functions, such as triangular, Gaussian, G-bell, etc. The choice of this function is intuitive and depends on the creator of the model. The number of observed variables also depends on the number of criteria, i.e., it represents the GRC values for each of them with an output of GFRG. Then, a set of IF-THEN rules is formulated to represent the relationships between the GRC input values and the GFRG output. The inference mechanisms used are the Mamdani and Sugeno methods, with the Mamdani method being used more frequently due to its simplicity [34]. The chosen inference engine performs fuzzy inference based on fuzzy rules, while a defuzzification method is used to transform the fuzzy output.

Considering the importance of this problem, numerous researchers deal precisely with the problem of machine selection. The process of machine selection is influenced by many factors, such as machining time, productivity, surface quality, accuracy and other technological features. Therefore, the process is specific to an individual company and cannot be generalized. The machine selection problem must be carefully evaluated using MCDM technique because of the many factors involved for a company in selecting a machine. Accordingly, the basic objective of the research in this paper refers to the technological analysis of the three machining processes, PAM, LBM and AWJM, used to cut various thicknesses steel sheets. Among the various technological aspects or technological criteria, the machine type, cutting speed, and thickness of the workpiece are the input factors. On the other hand, machining time, dimensional accuracy, kerf width, and surface roughness are used as output parameters. In order to create an intelligent decision-making system, a GFA is used to select cutting process from the aspect of the previously mentioned technological parameters. Reviewing the literature in the field of non-conventional machining methods, it was found that few studies are based on the analysis of machining performance as in this study. The main contribution to this research is reflected in the application of the intelligent decision system. In addition, the method for developing a fuzzy model, i.e., a rule base with more than three input variables, is presented. The advantage of the mirror method is the easy integration into any decision-making system and the updating of data without creating a new model. Based on the obtained results, the proposed methodology can be successfully applied to other machining methods.

2. Materials and Methods

The experiments in this study were intended to facilitate the decision for a machine tool depending on the technological parameters of the processes. For this purpose, three different unconventional machine tools were used to cut the material. In addition to the machine tools, the cutting speed and the thickness of the workpiece material also varied. grey relational analysis (GRA) is applied for the optimal selection of the machining tool based on categorical and numerical parameters such as machine type, cutting speed, and thickness of the workpiece to obtain the best characteristics in terms of machining time, dimensional accuracy, kerf width, and surface roughness. The steps for the GRA are shown in Figure 1. In this work, performance data such as machining time (MT), dimensional accuracy (DA), kerf width (KW), and surface roughness (SR) were studied.

2.1. Experimental Setup

Steel plates made of S235JR were selected for the experiments. This material is a very common carbon steel, which is used in many areas of industry for various purposes. The chemical composition and properties of S235JR steel are listed in Tables 1 and 2, respectively. Three different plate thicknesses of 5, 8, and 10 mm were used as workpiece.

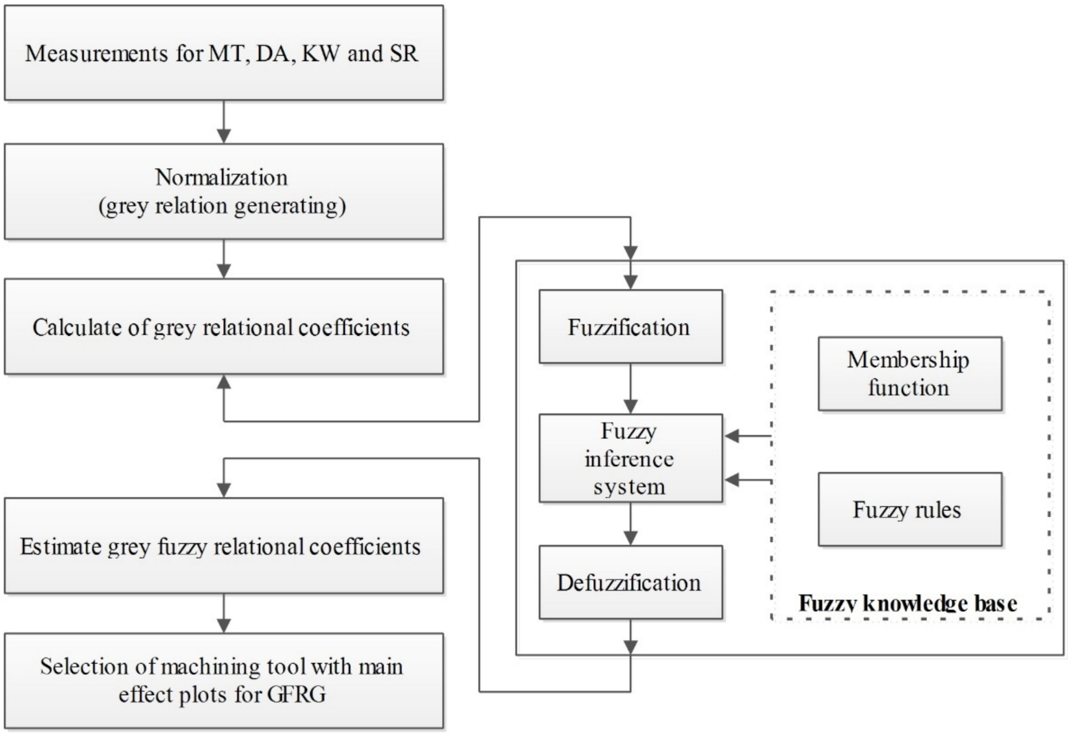

Figure 1. Flowchart of the research methodology.

Table 1. The chemical composition of S235JR, wt.%.

C	Mn	Cu	Al	Mo	Si	P	S	Fe
0.16	0.4	0.03	0.04	0.03	0.016	0.05	0.017	rest

Table 2. Properties of S235JR.

Material	Yield Point [MPa]	Tensile Strength [MPa]	A [%]	KV [J]	HV0.5
S235JR	335	440	33	45	148.5

To study the influence of machining tools under different machining conditions on the technological parameters, three non-conventional machines were used. Plasma arc machining (PAM), laser beam machining (LBM), and abrasive waterjet machining (AWJM) were used as experimental machines in this study (Table 3). These machines are generally used to cut metal as part of unconventional machining processes. The main characteristic of these machines is that none of them have a defined tool geometry, so the geometric accuracy of the machine is questionable. This is one of the main reasons for comparing these machines.

Table 3. Types of machining tools.

Machine Tool	Type	Workspace [mm]	Workpiece Thickness, max. [mm]	Accuracy [mm]	Power [kW]
PAM	OxyCut EkoFan N2	1500 × 3500	35	0.15	20
LBM	Bystar 3015	3000 × 1500	20	0.1	50
AWJM	STM WS1015	1300 × 2500	100	0.1	35

The cutting speed for each machine was determined based on a minimum, average, and maximum value available at the machine. The reason for this is to focus on the productivity of each machine from a machining time standpoint. For PAM, the cutting speeds are 1510, 2000, and 3620 mm/min; for LBM 900, 1100, and 2270 mm/min; AWJM 75, 120, and 270 mm/min.

The basic technological parameters of the machining process are productivity and machining quality. Machining quality is a complex indicator of the accuracy and surface quality of the production of the elementary part and must meet the minimum functional and operational requirements of the observed product. Machining productivity defines the quantity of goods produced, with the logical objective being the maximum result. In this work, performance data such as machining time (MT), dimensional accuracy (DA), kerf width (KW) and surface roughness (SR) were studied. MT is monitored directly from the machine tool display for each machining operation. That is, the total time required to cut all geometric shapes. Since the primary goal of the industry is to produce the product quickly and with a good surface quality, the next parameter that is monitored is SR. The arithmetic average roughness is used as an indicator of surface quality. The Mytutoyo SJ210 is used to measure this parameter. From the point of view of workpiece accuracy, the parameters DA and KW are very important. These parameters were measured after the experiments with microscope and camera using the calibration ruler DIV 0.01 mm. DA indicates how well a cut geometric element matches the size and specifications according to the drawing. On the other hand, KW is the width of the cut made with a plasma, laser, or water jet.

With the aim of obtaining a few geometries of the applied different machining tools, basic geometric shapes were adopted in the form of a circle, a hexagon, a combination of circle and rectangle, and a square, Figure 2.

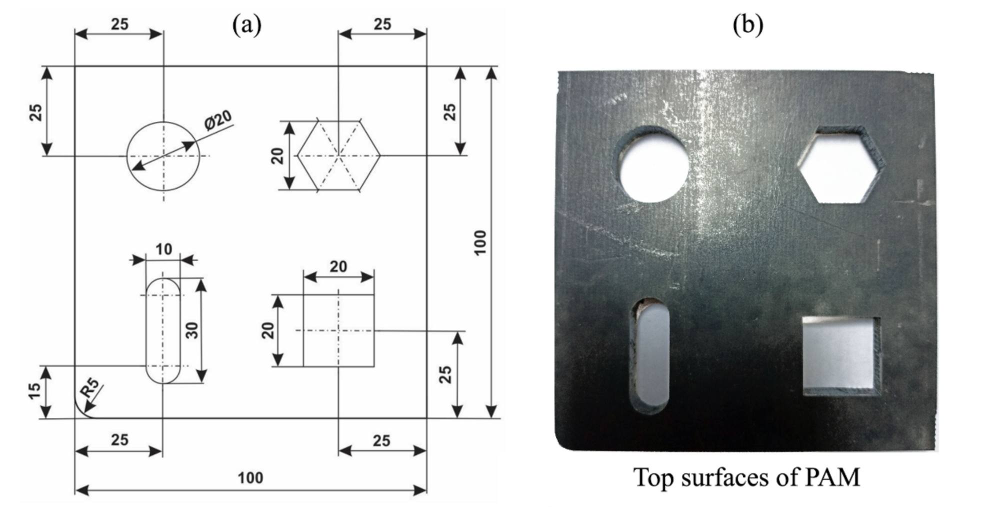

Figure 2. Basic geometric shapes for cutting: (**a**) 2D geometric shapes and (**b**) example of a PAM cut piece.

Quarter shapes of 100 × 100 mm are cut on each machine tool. Outer and all inner contours (inner geometric shapes) are cut clockwise. The aforementioned geometric shapes were used to determine the dimensional accuracy and kerf width for each type of machining. Cutting of each geometric shape as well as the base plate with dimensions of 100 × 100 mm was considered in the machining process. The surface roughness was measured at three positions of the cut surface. The first position is the distance from the top surface (1 mm for a 5 mm thick plate, 2 mm for an 8 mm thick plate, and 3 mm for a 10 mm thick plate). The second position is the center of the cut. Finally, the third position is identical to the first, only from the bottom side. An example of measurement when cutting 10 mm thick material by plasma processing is shown in Figure 3. The methodology for measuring the individual machining performances is shown in Figure 4.

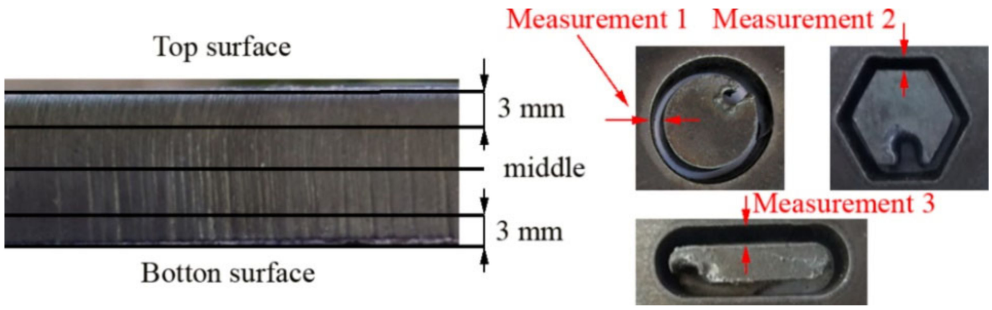

Figure 3. Example of three positions for measurement surface roughness and kerf width for thickness of 10 mm (PAM).

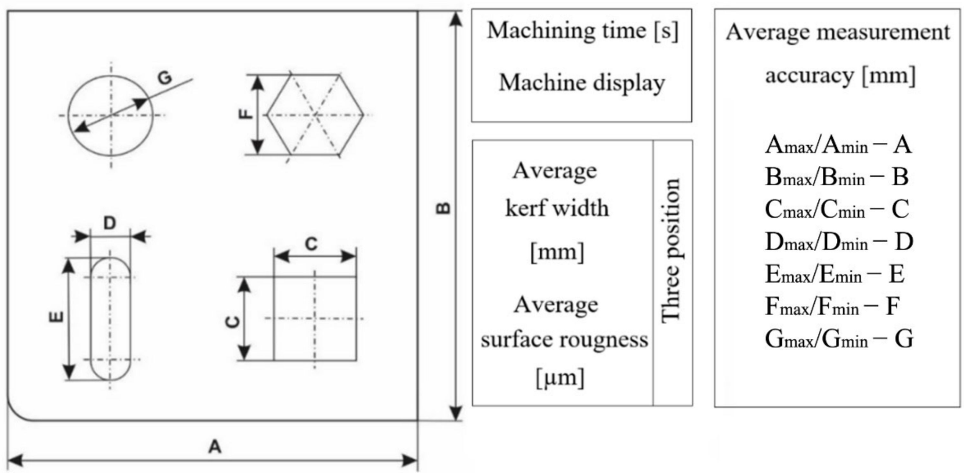

Figure 4. Methodology for measurement of various machining performances.

To compare machine tools, a special nine-point experimental design was performed. The systematized results of the experimental study of the efficiency of the different machine tools are presented in Table 4 below. In order to facilitate the presentation of the results for other technological parameters, the average values obtained by measurements at several points are given in addition to the machining time.

Table 4. Systematized results of measurements.

Exp. No.	Machine Tool	Cutting Speed [mm/min]	Workpiece Thickness	Machining Time [s]	Dimensional Accuracy [mm]	Kerf Width [mm]	Surface Roughness [μm]
1.	PAM	1510	10	64.3	0.486	2.890	3.522
2.	PAM	2000	8	56.3	0.607	3.420	2.512
3.	PAM	3620	5	42.2	0.740	3.910	4.223
4.	LBM	900	10	58.8	0.064	0.550	4.185
5.	LBM	1100	8	53.2	0.107	0.770	5.119
6.	LBM	2270	5	39.8	0.179	1.01	8.075
7.	AWJM	75	10	830.8	0.050	1.14	6.265
8.	AWJM	120	8	646.1	0.079	1.480	6.511
9.	AWJM	270	5	395.2	0.100	1.890	6.980

2.2. Grey Fuzzy Approach

In multi-criteria decision making, there are many methodologies that have been applied in various research [35,36]. However, the application of certain methods requires the analysis of data involved in the creation of the MCDM. Since the amount of data in this study is relatively small, the use of the Grey Fuzzy Approach is justified.

The combination of grey relational analysis (GRA) and fuzzy logic (FL) is applied to select the best machine tool that has the best quality characteristics considering multiple answers. GRA has gained great popularity in the field of optimization of multi-objective problems. This method essentially analyzes the degree of relationship of multiple attributes using certain equations [37], which are presented below.

To start the process, it is necessary to normalize the raw data into values from 0 to 1. Depending on the objective functions, whether maximum, nominal, or minimum, different normalization formulas apply. In this work, the objective function for all responses is minimum, so normalization is performed according to Equation (1).

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{1}$$

In the above equations $x_i^0(k)$ is original sequence, $x_i^*(k)$ sequence after preprocessing, $\max x_i^0(k)$ is the largest value $x_i^0(k)$ and smallest value of $x_i^0(k)$.

Based on the maximum normalized value, the deviation sequence is determined independently of the output variables [38]. This value is denoted by D and is given as a reference value in Equation (2). After preprocessing the data and determining the absolute difference between each normalized value and the reference value D, Equation (3), the grey relativity coefficient is calculated. The formula for the grey relational coefficient (GRC) is given in Equation (4).

$$D = \max\left(X_{ijk}\right) \tag{2}$$

$$\Delta_{ijk} = X_{ijk} - D \tag{3}$$

$$\gamma_i(k) = \frac{\Delta_{\min} + \gamma \cdot \Delta_{\max}}{\Delta_{oi}(k) + \gamma \cdot \Delta_{\max}},\ \gamma \in [0,1] \tag{4}$$

In Equation (4), $\Delta_{oi}(k)$ is $\Delta_{oi}(k)$ of reference sequence, γ distinguishing coefficient ($\gamma = 0.5$), when the kth feature is numeric. The $\Delta_{oi}(k)$ of reference sequence is calculated by Equation (5).

$$\Delta_{oi}(k) = \left\|x_0^*(k) - x_0^{*0}(k)\right\| \tag{5}$$

A grey relational grade is a weighted sum of the GRC and is defined in Equation (6).

$$\zeta_i = \frac{1}{n}\sum_{k=1}^{n} i\gamma_i(k) \tag{6}$$

The second part of the GFA represents the logical system consisting of fuzzification, fuzzy inference system (rule base and membership functions) and finally a defuzzification. Fuzzification means that the crisp input values of are converted into appropriate linguistic values. In this case, the GRC coefficient values from 0 to 1 are divided into fuzzy sets or linguistic values, for example, LOW, MEDIUM, and HIGH. The fuzzifier uses the Gbell membership function to fuzzify the GRC of each feature. The mathematical form of this function is shown in Equation (7).

$$triangle(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \tag{7}$$

This function has the task of changing the linguistic values between zero and one. In Equation (7), x indicates the range of input variables, and a, b, and c are the linguistic value parameters.

The generation of fuzzy rules (if-then rules) follows. The Mamdani fuzzy inference system (FIS) was developed in an effort to improve the systematic approach to generating fuzzy rules from a given input–output dataset. One of the main applications of the Mamdani FIS is when the consequences of the rules are fuzzy. This provides more flexibility to the fuzzy model for the grey fuzzy approach. The general structure of a fuzzy rule in a Mamdani fuzzy inference model [39] has the format, Equations (8) and (9), or in mathematical form:

$$IF\ X\ is\ A\ THEN\ Y\ is\ B \tag{8}$$

$$\{IF\ (premise_i)\ THEN\ (consequent_i)\}\ _{i=1}^{n} \tag{9}$$

Here, A and B are linguistic values defined by fuzzy sets on domains X and Y, respectively. The if-part of the rule "*X is A*" is called the antecedent or premise, while the then-part of the rule "*Y is B*" is called the consequent or conclusion. The input of an if-then rule is the current value of the input variable and the output is generally defuzzified.

The resulting fuzzy sets are combined from the inference value of each input rule using the aggregation operator. Depending on the system, it may not be necessary to evaluate every possible input combination, since some rarely or never occur. This type of evaluation, usually performed by an experienced operator, allows fewer rules to be evaluated, simplifying the processing logic and perhaps even improving the performance of the fuzzy logic system.

Finally, a defuzzification method is used to change the fuzzy inference output to a non-fuzzy value. The defuzzification is achieved using the Centroid defuzzification method (COA) under the membership function, Equation (10):

$$y' = \frac{\sum_{i=1}^{n} y_1 \mu_{Ei}(y)}{\sum_{i=1}^{n} \mu_{Ei}(y_1)} \tag{10}$$

where y' are the defuzzified outputs (the output for a given input vector predicted by the grey fuzzy relational grade GFRG values in this study); μEi and μFi = the aggregated memberships functions; y = the output variable (the center value of the regions). The fundamental role of fuzzy logic in this approach is that, based on the GRC coefficient of each input variable, the degree of fuzzy reasoning is determined. The maximum value of this coefficient is the best solution.

3. Results and Discussion

GRA is applied for optimal machining tool selection based on categorical and numerical parameters such as machine type, cutting speed, and workpiece thickness to obtain the best characteristics in terms of machining time, dimensional accuracy, kerf width, and surface roughness.

Therefore, the first step is to measure and systematize the output parameters as shown in Table 4. After the measurement of the physical quantities according to which each machine tool is evaluated, the second step of the grey relational analysis follows, namely normalization. It is well known that raw experimental data cannot be used for GRA. Therefore, these data should be processed in a quantitative way that is suitable for grey scale analysis. Then, the experimental data are converted into values between 0.00 and 1.00.

The third step is the calculation of the GRC, which consists of several steps. First, the signal-to-noise ratio must be determined, which indicates how the response changes relative to the nominal or target value under different noise conditions. There are two signal-to-noise ratios that are of general interest to GRA: Smaller-the-Better and Larger-the-Better. Since all output parameters tend to a minimum, the target value of all input parameters (MT, DA, KW, and SR) is the-lesser-the-better, then the normalized values of these parameters are calculated according to Equation (2). The results of normalized values, deviation sequences, grey correlation coefficients, and grey correlation degrees are shown in Table 5.

Table 5. Results of normalized values, deviation sequences, and grey relational coefficients.

No.	Machining Time [s] Smaller the Better			Dimensional Accuracy [mm] Smaller the Better			Kerf Width [mm] Smaller the Better			Surface Roughness [µm] Smaller the Better			Relational Grade	
	Norm.	Dev.	GRC	Norm.	Dev.	GRC	Norm.	Dev.	GRC	Norm.	Dev.	GRC	GFRG	Rank
1.	0.9690	0.0310	0.7259	0.3709	0.6291	0.1153	0.3036	0.6964	0.1054	0.8184	0.1816	0.4671	0.218	7
2.	0.9791	0.0209	0.7972	0.1962	0.8038	0.0926	0.1458	0.8542	0.0876	1.0000	0.0000	1.0000	0.498	3
3.	0.9970	0.0030	0.9643	0.0000	1.0000	0.0758	0.0000	1.0000	0.0758	0.6924	0.3076	0.3410	0.142	6
4.	0.9760	0.0240	0.7775	0.9798	0.0202	0.8024	1.0000	0.0000	1.0000	0.6993	0.3007	0.3470	0.728	1
5.	0.9831	0.0169	0.8288	0.9177	0.0823	0.4993	0.9345	0.0655	0.5561	0.5314	0.4686	0.2535	0.501	2
6.	1.0000	0.0000	1.0000	0.8139	0.1861	0.3058	0.8631	0.1369	0.3746	0.0000	1.0000	0.1373	0.497	4
7.	0.0000	1.0000	0.0758	1.0000	0.0000	1.0000	0.8244	0.1756	0.3184	0.3254	0.6746	0.1909	0.379	5
8.	0.2335	0.7665	0.0967	0.9582	0.0418	0.6621	0.7232	0.2768	0.2286	0.2811	0.7189	0.1812	0.368	8
9.	0.5507	0.4493	0.1544	0.9278	0.0722	0.5320	0.6012	0.3988	0.1706	0.1968	0.8032	0.1654	0.368	9

In the preceding methodology, each output parameter is classified as a “smaller-better” quality attribute. The results presented have a certain degree of uncertainty. It is such data that lends itself to further processing using fuzzy logic. Thus, the complicated multi-objective problem of machine tool selection can be solved by integrating GRA and FL.

According to previous research, Mamdani inference system is the most commonly used. Apart from the fact that the rule base is intuitive and easier to interpret, there are two main reasons for its use. The first is that it allows manual adjustment of the input functions, and the second is that the output is also in the form of a fuzzy set. It is capable of processing numerical data and linguistic knowledge simultaneously.

The Mamdani inference system was used to determine the grey fuzzy relation coefficient. The methodology is divided into four phases. Since fuzzy logic uses linguistic variables, the first phase involved the selection of input/output variables represented in the linguistic format. The selection of fuzzy intervals is an intuitive procedure that depends on the experience of the fuzzy modeler. It has been shown that it is best to divide an input variable into three intervals, for example, low, medium, and high. The linguistic variables for input and output with their fuzzy intervals are listed in Table 6.

Table 6. Inputs, outputs, linguistic values, and fuzzy intervals.

No.	System Linguistic Variable	Variables	Linguistic Values	Fuzzy Interval
1.	Input	GRC for MT	Low	0.2 3 0
			Medium	0.2 3 0.5
			High	0.2 3 1
2.		GRC for DA	Low	0.2 3 0
			Medium	0.2 3 0.5
			High	0.2 3 1
3.		GRC for KW	Low	0.2 3 0
			Medium	0.2 3 0.5
			High	0.2 3 1
4.		GRC for SR	Low	0.2 3 0
			Medium	0.2 3 0.5
			High	0.2 3 1
5.	Output	Grey fuzzy relation grade—GFRG	Very low	0.2 3 0
			Low	0.2 3 0.5
			Medium	0.2 3 1

The selection of membership functions for input and output variables represents the second phase. Fuzzy intervals are determined based on the intuition and experience of the creator of the fuzzy model. A more accurate model can be generated by using more MFs. However, the time needed to create the rules increases and the interpretability of the model deteriorates. An example of such a function is a Gbell function. In modelling the GRG in this research, the Gbell type of membership functions is used. The membership functions of GRC for MT are shown in Figure 5. The same form and membership function parameters are used for the other input parameters. Figure 6 shows the output membership functions for GFRG.

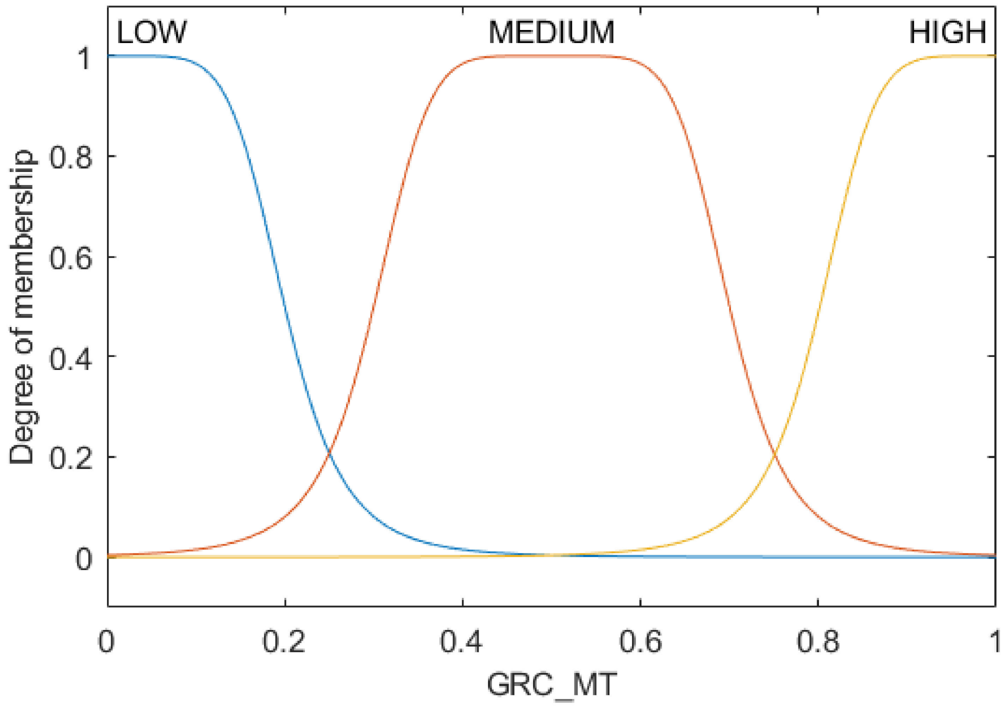

Figure 5. Example of Gbell membership function of GRC for MT.

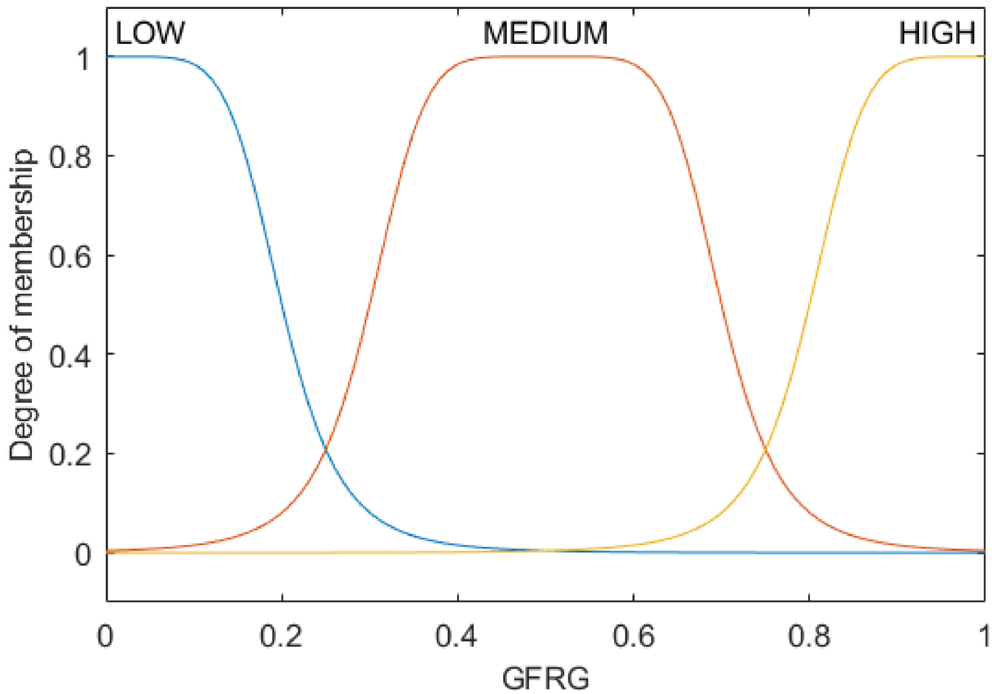

Figure 6. Example of Gbell membership function of GFRG.

The third phase of the grey fuzzy relationship analysis involves the creation of fuzzy rules according to the experimental design. After determining the fuzzification, the input data with the conditions of the rules are determined and evaluated. The essential part of the fuzzy rule inference system is a set of IF-THEN linguistic rules that have the form

"If (GRC_MT is HIGH) and (GRC_DA is LOW) and (GRC_KW is LOW) and (GRC_SR is MEDIUM) then (GFRG is LOW)", where the first four terms in parentheses (antecedents) are grey relational coefficients containing linguistic variables. The fifth parenthesis represents the consequence. Starting from a larger grey relational coefficient indicating better performance characteristics, nine fuzzy rules are formed as shown in Table 7.

Table 7. Display rules using linguistic expressions.

Fuzzy Rule Base
1. If (GRC_MT is HIGH) and (GRC_DA is LOW) and (GRC_KW is LOW) and (GRC_SR is MEDIUM) then (GFRG is LOW)
2. If (GRC_MT is HIGH) and (GRC_DA is LOW) and (GRC_KW is LOW) and (GRC_SR is HIGH) then (GFRG is MEDIUM)
3. If (GRC_MT is HIGH) and (GRC_DA is LOW) and (GRC_KW is MEDIUM) and (GRC_SR is HIGH) then (GFRG is MEDIUM)
4. If (GRC_MT is HIGH) and (GRC_DA is HIGH) and (GRC_KW is HIFH) and (GRC_SR is LOW) then (GFRG is HIGH)
5. If (GRC_MT is HIGH) and (GRC_DA is MEDIUM) and (GRC_KW is MEDIUM) and (GRC_SR is LOW) then (GFRG is MEDIUM)
6. If (GRC_MT is HIGH) and (GRC_DA is MEDIUM) and (GRC_KW is MEDIUM) and (GRC_SR is LOW) then (GFRG is MEDIUM)
7. If (GRC_MT is HIGH) and (GRC_DA is MEDIUM) and (GRC_KW is MEDIUM) and (GRC_SR is LOW) then (GFRG is MEDIUM)
8. If (GRC_MT is MEDIUM) and (GRC_DA is MEDIUM) and (GRC_KW is MEDIUM) and (GRC_SR is MEDIUM) then (GFRG is MEDIUM)
9. If (GRC_MT is LOW) and (GRC_DA is MEDIUM) and (GRC_KW is LOW) and (GRC_SR is LOW) then (GFRG is MEDIUM)

Between antecedents, the AND operator is used. Two built-in AND methods are supported in the fuzzy logic toolbox: MIN (minimum) and PROD (product). When building the fuzzy model, both methods were tried, but the MIN operator resulted in a higher GFRG coefficient. Moreover, better results were obtained by using PROD implication method and SUM aggregation. Finally, the area centroid defuzzification technique is applied to convert the fuzzy numbers into crisp real numbers. The value of the fuzzy numbers can be found in the penultimate column of Table 6. Table 8 shows the characteristics of the fuzzy inference system used to calculate the GFRG.

Table 8. Properties of fuzzy inference system to calculate GFRG.

Name	"MCDM1"
FIS type	Mamdani
And Method	"min"
Implication Method	"prod"
Aggregation Method	"sum"
Defuzzification Method	"centroid"
Inputs	[1×4]
Outputs	[1×1]
Rules	[1×9]

One of the advantages of the fuzzy model is the 3D representation, which can also be used for easier decision making, especially when a large amount of data are involved. The 3D surface representation is used to study the variation of the response with respect to two predicted parameters, while keeping the other two parameters at constant values (recommendation: maximum values). Figure 7 shows the 3D surface plots for the response GFRG with respect to two predicted GRC parameters, in this case GRCs for DA and KW. From this figure, it can be concluded that as GRC-DA and GRC-KW increase from a low to a high level, GFRG also increases.

Mean GFRG parameters were calculated and shown in Table 3. The highest value of the mean GFRG response of the parameters was obtained when cutting a steel sheet with a thickness of 10 mm with LBM at the minimum cutting speed set on the machine. LBM was also selected for cutting a sheet with a thickness of 8 mm and 5 mm, but at a medium and maximum cutting speed, respectively. Although AWJM machining is often used for cutting steel in production, it proved to be the worst in this case due to the excessive machining time.

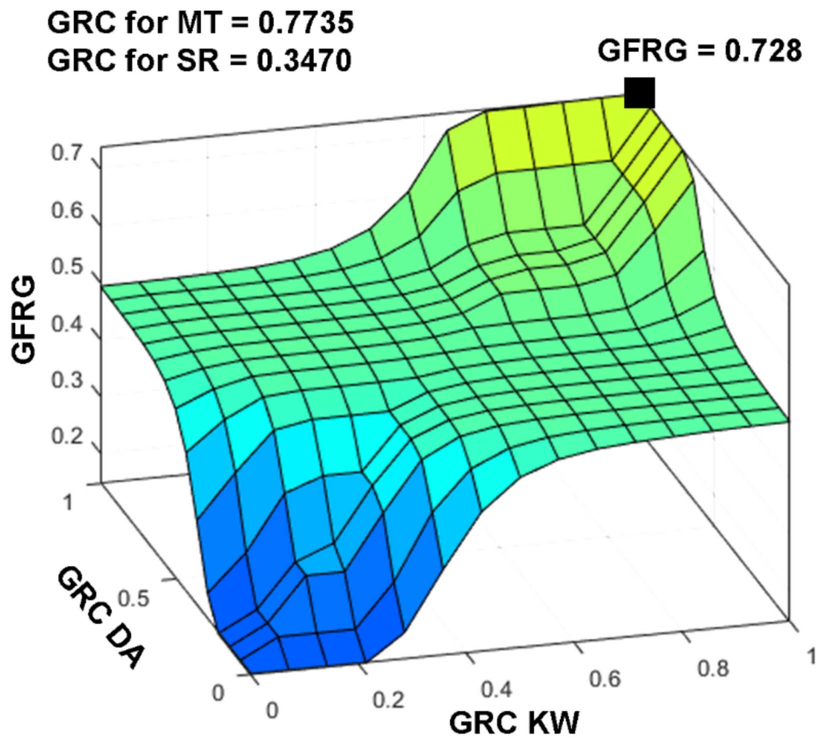

Figure 7. 3D surface plot of GFRG.

To test the similarity between the means of the level of the main factors, such as the type of cutting process, a main effect diagram was used. This diagram shows the effects of the main factors and their interaction on GFRG. In the main effects plot, it can be seen that the steep slope of the cutting process is the property that has the greatest influence on the estimation of GFRG, Figure 8. By observing the slope of the curve, i.e., the mean values, an analysis with fuzzy 3D diagrams was confirmed. It is concluded that the presented processing conditions are the most suitable for LBM from the point of view of technological parameters.

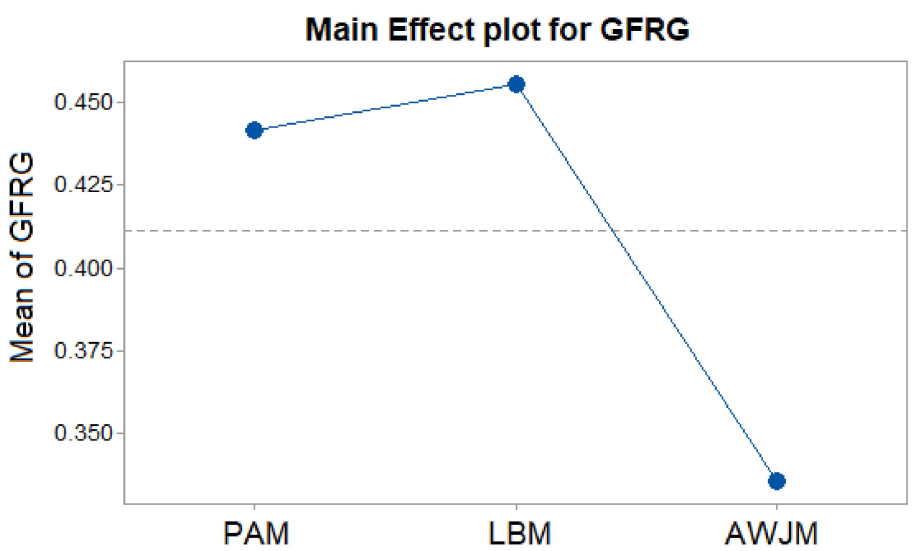

Figure 8. Main effect plot of GFRG.

The same problem of selecting machine tools for non-conventional processes with multiple alternatives has also been solved by previous researchers [25–27]. Methods such as fuzzy—AHP or fuzzy—TOPSIS were mainly used. The results of the rankings mostly depended on the way the criteria were selected. The parameters from the machine tool catalog, such as accuracy, surface roughness, cost, etc., are mainly selected as criteria. Unlike that, experimentally determined values are used as criteria in this study.

In summary, the advantage of the evaluation model developed in this study over the previously proposed method is that it can be very easily integrated into any decision-making system. Thus, the results of the decision do not have to be based only on the opinion of experts, but also on the actual performance of the machine tools included in the analysis. This helps to improve the overall performance of the observed production process. Due to the flexibility of fuzzy logic, the model obtained in this way can be additionally updated at any time with new data, new machine tools and the like. Moreover, the proposed model of a grey fuzzy approach shows its advantage in flexibility with respect to the preferences of the decision makers.

A possible application of the hybrid method GFA proposed in this paper can be found in Industry 4.0, a concept that includes, among other things, automatic control to ensure the reliability and stability of the observed systems. In other words, the classical decision-making models are not adapted to the Industry 4.0 technology. Therefore, attention is paid to the application of artificial intelligence methods [40]. The grey relations approach is represented in a fuzzy system, which provides better flexibility of the model and better integration with intelligent decision systems. The development of the hybrid MCDM model enables the selection strategy of machine tools, and by integrating it into a more comprehensive system, it can be implemented in automatic control. Moreover, the complex imprecise and non-numerical information included in the proposed methodology can be improved with enhanced intelligence-oriented algorithms, which increases its authenticity and stability. The approach proposed in this paper can be applied to other problems where it is necessary to make correct decisions. Based on the presented research and review of numerous literatures, ideas for future research are proposed. Since the fuzzy logic-based model is flexible, one could easily incorporate more machine tools, more types of materials, a wider range of cutting speeds, etc., into the model. In addition, other technological parameters such as state of surface, microhardness, etc., can also be included.

4. Conclusions

This paper investigates the influence of various attributes such as machining time, dimensional accuracy, kerf width, and surface roughness on the selection of the best machine tools (Plasma Arc Machining—PAM, Laser Beam Machining—LBM, Abrasive Water Jet Machining—AWJM). For this purpose, the grey relational analysis is applied. First, grey relational analysis was applied, which was necessary to normalize the raw data into values from 0 to 1. Then, a fuzzy logic system was used, consisting of a fuzzification, a fuzzy inference system (rule base and membership functions), and finally a defuzzification. The analysis of the fuzzy model showed that the laser machining is the most suitable for cutting steel plates with a thickness of 8 and 10 mm, while the plasma machining is recommended for a thickness of 5 mm, from the aspects of machining time, dimensional accuracy, and surface quality. The obtained results are appropriate only in the context of this research. The proposed hybrid multi-criteria method, which includes GRA and FL, has been concretely applied in a manufacturing company. Due to its flexibility, it can be very easily integrated into the Industry 4.0 system. Future research should be based on the extension of the decision model by introducing other cutting methods, other materials and other machining performances.

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Nomenclature

MCDM	multi-criteria decision making
GFA	grey fuzzy approach
GRA	grey relational analysis
FL	fuzzy logic
PAM	plasma arc machining
LBM	laser beam machining
AWJM	abrasive waterjet machining
MT	machining time
DA	dimensional accuracy
KW	kerf width
SR	surface roughness
GRC	grey relational coefficient
GRG	grey relational grade
GFRG	grey fuzzy relational grade
FIS	fuzzy inference system
COA	centroid defuzzification method

References

1. Komatsu, W.; Nakamoto, K. Machining process analysis for machine tool selection based on form-shaping motions. *Precis. Eng.* **2021**, *67*, 199–211. [CrossRef]
2. Elsheikh, A.H.; Guo, J.; Huang, Y.; Ji, J.; Lee, K.-M. Temperature field sensing of a thin-wall component during machining: Numerical and experimental investigations. *Int. J. Heat Mass Transf.* **2018**, *126*, 935–945. [CrossRef]
3. Ižol, P.; Varga, J.; Vrabel', M.; Demko, M.; Greš, M. Evaluation of 3-axis and 5-axis milling strategies when machining freeform surface features. *J. Prod. Eng.* **2022**, *25*, 1–4. [CrossRef]
4. Manjaiah, M.; Narendranath, S.; Basavarajappa, S. Review on non-conventional machining of shape memory alloys. *Trans. Nonferrous Met. Soc. China* **2014**, *24*, 12–21. [CrossRef]
5. Devaraj, R.; Abouel Nasr, E.; Esakki, B.; Kasi, A.; Mohamed, H. Prediction and analysis of multi-response characteristics on plasma arc cutting of Monel 400™ alloy using mamdani-fuzzy logic system and sensitivity analysis. *Materials* **2020**, *13*, 3558. [CrossRef] [PubMed]
6. Venkatesh, N.; Sabari Sriram, S.; Satish Chandran, V.; Ramesh Babu, A. Effect of Geometrical and Process Parameters on Utilization of Sheet Material in Plasma and Laser Cutting Processes. In *Advances in Forming, Machining and Automation*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 613–624.
7. Madić, M.; Petrović, G.; Petković, D.; Antucheviciene, J.; Marinković, D. Application of a Robust Decision-Making Rule for Comprehensive Assessment of Laser Cutting Conditions and Performance. *Machines* **2022**, *10*, 153. [CrossRef]
8. Hossain, A.; Hossain, A.; Nukman, Y.; Hassan, M.; Harizam, M.; Sifullah, A.; Parandoush, P. A fuzzy logic-based prediction model for kerf width in laser beam machining. *Mater. Manuf. Process.* **2016**, *31*, 679–684. [CrossRef]
9. Pahuja, R.; Ramulu, M.; Hashish, M. Surface quality and kerf width prediction in abrasive water jet machining of metal-composite stacks. *Compos. Part B Eng.* **2019**, *175*, 107134. [CrossRef]
10. Petrović, G.; Pavlović, J.; Madić, M.; Marinković, D. Optimal Synthesis of Loader Drive Mechanisms: A Group Robust Decision-Making Rule Generation Approach. *Machines* **2022**, *10*, 329. [CrossRef]
11. Qudeiri, J.E.A.; Zaiout, A.; Mourad, A.-H.I.; Abidi, M.H.; Elkaseer, A. Principles and characteristics of different EDM processes in machining tool and die steels. *Appl. Sci.* **2020**, *10*, 2082. [CrossRef]
12. Çınar, Z.M.; Abdussalam Nuhu, A.; Zeeshan, Q.; Korhan, O.; Asmael, M.; Safaei, B. Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability* **2020**, *12*, 8211. [CrossRef]

13. Çimren, E.; Çatay, B.; Budak, E. Development of a machine tool selection system using AHP. *Int. J. Adv. Manuf. Technol.* **2007**, *35*, 363–376. [CrossRef]
14. Chatterjee, P.; Chakraborty, S. A comparative analysis of VIKOR method and its variants. *Decis. Sci. Lett.* **2016**, *5*, 469–486. [CrossRef]
15. Karim, R.; Karmaker, C. Machine selection by AHP and TOPSIS methods. *Am. J. Ind. Eng.* **2016**, *4*, 7–13.
16. Maity, S.R.; Chakraborty, S. Tool steel material selection using PROMETHEE II method. *Int. J. Adv. Manuf. Technol.* **2015**, *78*, 1537–1547. [CrossRef]
17. Kabak, M.; Dagdeviren, M. A hybrid approach based on ANP and grey relational analysis for machine selection. *Teh. Vjesn. Tech. Gaz.* **2017**, *24*, 109–118.
18. Wu, Z.; Ahmad, J.; Xu, J. A group decision making framework based on fuzzy VIKOR approach for machine tool selection with linguistic information. *Appl. Soft Comput.* **2016**, *42*, 314–324. [CrossRef]
19. Ayağ, Z.; Özdemir, R.G. A fuzzy AHP approach to evaluating machine tool alternatives. *J. Intell. Manuf.* **2006**, *17*, 179–190. [CrossRef]
20. Li, H.; Wang, W.; Fan, L.; Li, Q.; Chen, X. A novel hybrid MCDM model for machine tool selection using fuzzy DEMATEL, entropy weighting and later defuzzification VIKOR. *Appl. Soft Comput.* **2020**, *91*, 106207. [CrossRef]
21. Hafezalkotob, A.; Hafezalkotob, A. Interval target-based VIKOR method supported on interval distance and preference degree for machine selection. *Eng. Appl. Artif. Intell.* **2017**, *57*, 184–196. [CrossRef]
22. Farhan, U.H.; Tolouei-Rad, M.; Osseiran, A. Use of AHP in decision-making for machine tool configurations. *J. Manuf. Technol. Manag.* **2016**, *27*, 874–888. [CrossRef]
23. Aghdaie, M.H.; Zolfani, S.H.; Zavadskas, E.K. Decision making in machine tool selection: An integrated approach with SWARA and COPRAS-G methods. *Eng. Econ.* **2013**, *24*, 5–17.
24. Perçin, S.; Min, H. Optimal machine tools selection using quality function deployment and fuzzy multiple objective decision making approach. *J. Intell. Fuzzy Syst.* **2013**, *24*, 163–174. [CrossRef]
25. Şengül, A.B. Fuzzy AHP in selecting cutting technology for AISI 1040 steel used in manufacturing the tractor back lifting stand system. *High Temp. Mater. Process. Int. Q. High-Technol. Plasma Process.* **2015**, *19*, 1–16. [CrossRef]
26. Khan, A.; Maity, K.P. Application of MCDM-based TOPSIS method for the optimization of multi quality characteristics of modern manufacturing processes. *Int. J. Eng. Res. Afr.* **2016**, *23*, 33–51. [CrossRef]
27. Temuçin, T.; Tozan, H.; Vayvay, Ö.; Harničárová, M.; Valíček, J. A fuzzy based decision model for nontraditional machining process selection. *Int. J. Adv. Manuf. Technol.* **2014**, *70*, 2275–2282.
28. Kumari, A.; Acherjee, B. Selection of non-conventional machining process using CRITIC-CODAS method. *Mater. Today Proc.* **2022**, *56*, 66–71. [CrossRef]
29. Elsheikh, A.H.; Abd Elaziz, M.; Das, S.R.; Muthuramalingam, T.; Lu, S. A new optimized predictive model based on political optimizer for eco-friendly MQL-turning of AISI 4340 alloy with nano-lubricants. *J. Manuf. Process.* **2021**, *67*, 562–578. [CrossRef]
30. Elsheikh, A.H.; Abd Elaziz, M.; Vendan, A. Modeling ultrasonic welding of polymers using an optimized artificial intelligence model using a gradient-based optimizer. *Weld. World* **2022**, *66*, 27–44. [CrossRef]
31. Samvedi, A.; Jain, V.; Chan, F.T. An integrated approach for machine tool selection using fuzzy analytical hierarchy process and grey relational analysis. *Int. J. Prod. Res.* **2012**, *50*, 3211–3221. [CrossRef]
32. Nguyen, H.-T.; Dawal, S.Z.M.; Nukman, Y.; Aoyama, H. A hybrid approach for fuzzy multi-attribute decision making in machine tool selection with consideration of the interactions of attributes. *Expert Syst. Appl.* **2014**, *41*, 3078–3090. [CrossRef]
33. Alsoruji, G.; Muthuramalingam, T.; Moustafa, E.B.; Elsheikh, A. Investigation and TGRA based optimization of laser beam drilling process during machining of Nickel Inconel 718 alloy. *J. Mater. Res. Technol.* **2022**, *18*, 720–730. [CrossRef]
34. Wu, Y.; Zhou, F.; Kong, J. Innovative design approach for product design based on TRIZ, AD, fuzzy and Grey relational analysis. *Comput. Ind. Eng.* **2020**, *140*, 106276. [CrossRef]
35. Muthuramalingam, T.; Akash, R.; Krishnan, S.; Phan, N.H.; Pi, V.N.; Elsheikh, A.H. Surface quality measures analysis and optimization on machining titanium alloy using CO_2 based laser beam drilling process. *J. Manuf. Process.* **2021**, *62*, 1–6. [CrossRef]
36. Khoshaim, A.B.; Moustafa, E.B.; Bafakeeh, O.T.; Elsheikh, A.H. An optimized multilayer perceptrons model using grey wolf optimizer to predict mechanical and microstructural properties of friction stir processed aluminum alloy reinforced by nanoparticles. *Coatings* **2021**, *11*, 1476. [CrossRef]
37. Deng, J. Introduction to grey theory system. *J. Grey Syst.* **1989**, *1*, 1–24.
38. Hashemi, H.; Mousavi, S.M.; Zavadskas, E.K.; Chalekaee, A.; Turskis, Z. A new group decision model based on grey-intuitionistic fuzzy-ELECTRE and VIKOR for contractor assessment problem. *Sustainability* **2018**, *10*, 1635. [CrossRef]
39. Mamdani, E.H. Applications of fuzzy algorithms for control of simple dynamic plant. *Proc. IEE* **1974**, *121*, 1585–1588. [CrossRef]
40. Elsheikh, A. Bistable Morphing Composites for Energy-Harvesting Applications. *Polymers* **2022**, *14*, 1893. [CrossRef] [PubMed]