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A Novel Decision Support System Based on Fuzzy Multi Criteria Decision Making for Optimizing Machining Parameters

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ABSTRACT

The aim of this study is to develop a novel decision support system to optimize machining parameters. We combine three distinct methods: experimental design and analysis, fuzzy data envelopment analysis (DEA), and fuzzy analytical hierarchy process (AHP). First, a full factorial experiment, including four factors and three levels, was conducted. We considered the cutting speed, feed rate, depth of cut, and number of cutting tool inserts, as factors. The following three outputs were selected: material removal rate, machining time, and surface roughness. Second, 23 experiments were determined to be efficient decision-making units using fuzzy DEA with a super-efficiency method. Finally, a fuzzy AHP approach was employed to rank the efficient experiments. In conclusion, the results show that the fuzzy DEA-fuzzy AHP and fuzzy DEA with super-efficiency generate clearly different rankings of experiments, and the fuzzy DEA-fuzzy AHP approach outperformed the fuzzy DEA with super-efficiency approach. The results highlighted the importance of considering expert opinions in decision-making processes.

Keywords: Decision Support System; Experimental Analysis; Fuzzy Analytical Hierarchy Process; Fuzzy Data Envelopment Analysis; Fuzzy Multi Criteria Decision Making; Machining.

INTRODUCTION

AISI 4140 steel is one of the most commonly used alloys in several industries, especially the automotive and aerospace industries, because it has a variety of characteristic features such as weldability, good formability, excellent corrosion resistance, and high strength. In addition, machinery, parts and apparatus, agricultural vehicles, numerous products employed in defense areas, and the petroleum and derivatives industry use AISI 4140 steel. Machining operations are performed on the material using different methods because it has a very wide area of application (Şahinoğlu and Rafighi (2020), Gürbüz and Gönülaçar (2020), Schwalm et al. (2020), and Lubis et al. (2020)).

Cost, time, and quality are the most important factors that affect manufacturing productivity. To adapt to new technologies and survive in competitive markets, the variables affecting these factors must be controlled. CNC milling is a traditional machining method frequently used in manufacturing and other industrial sectors. Several studies have focused on cutting parameters to improve the quality of machining processes in milling. Milling performance mainly depends on the selection of the most appropriate input parameters to optimize various objective functions, such as maximizing the material removal rate (MRR) and minimizing the machining time (Tm) and surface roughness (Ra) (Kumar and Verma, 2020). Most deformations occurring between tools and materials during machining cause certain difficulties in achieving the desired optimization goals because of the interaction of many factors. To overcome these problems, researchers have suggested various approaches to optimize cause-effect relationships between various factors and targeted product characteristics with multiple responses (Al-Refaie et al., 2014).

Several studies have been conducted for the optimization of machining parameters. The studies were designed according to experimental design methods (i.e., full factorial, Taguchi, etc.), and the main and interaction effects were analyzed; for example, Fedai et al. (2018) and Kahraman et al. (2018). In general, single- and multiple-response optimization studies have been conducted; for example, Ananthakumar et al. (2019), Sharma et al. (2019) and Basar et al. (2019). However, fuzzy environment has not been considered. On the other hand, multiple replications are performed for each experiment in the studies. Thus, more than one value is generated for each output. In this case, the study did not have exact values and had average and standard deviation values. These circumstances suggest that future studies should employ a fuzzy-logic approach to overcome this type of uncertainty. In several studies, the optimum values of the input parameters were determined either by data envelopment analysis or by multi criteria decision-making (MCDM) methods (i.e., TOPSIS, PROMETHEE, or analytical hierarchy process (AHP)) using the inputs and outputs obtained from the experimental analysis (Manoj et al. (2018); Chakraborty et al. (2019); Phan and Muthuramalingam (2020); Naik et al. (2020); Basar et al. (2020)). In other studies, the criterion weights were calculated using the AHP method, and the weights were then embedded into other multi criteria decision-making methods, such as those of Singaravel and Selvaraj (2015), Nadda et al. (2020), and Kumar and Verma (2020). However, our study differs from the literature in the following ways. 1) A total of 81 experiments were conducted using a full factorial experimental analysis. Three replications for surface roughness were performed for each experiment and output values were obtained; 2) in our optimization stages, the uncertainty and fuzzy environment caused by different output values obtained from the replications were considered; and 3) efficient experiments determined by the fuzzy data envelopment analysis (DEA) approach were optimized using the fuzzy AHP method, based on expert opinions. No previous study has applied this approach for the optimization of machining parameters. This study fills this gap in the literature.

The remainder of the paper is organized as follows. Section 2 describes the proposed decision support system and explains the methodologies (i.e., experimental design and analysis, fuzzy data envelopment analysis, and fuzzy analytical hierarchy process) in detail. Section 3 discusses the results and Section 4 concludes the paper.

THE PROPOSED DECISION SUPPORT SYSTEM

In this study, we combined the following three methods to develop a decision support system (refer Figure 1) to optimize machining parameters: experimental design and analysis, fuzzy data envelopment analysis (DEA), and fuzzy analytical hierarchy process (AHP). First, a full-factorial experiment (3^4 =81) was designed. The experimental design consisted of four factors (cutting speed, feed rate, cut depth, and number of cutting tool inserts) and three levels. Three output parameters (material removal rate, surface roughness, and machining time) were measured. Second, all inputs and generated outputs in the experimental design and analysis were fed into the fuzzy data envelopment analysis models. Thus, efficient decision making units (i.e., experiments) were determined. Finally, efficient experiments were conducted in terms of a multi criteria decision making problem to optimize the multi-response problem and rank alternatives by considering expert opinions. Thus, this decision support system can assess and compare machining parameters in a fuzzy environment. The main contribution of this study is the development of a decision support system by integrating the three distinct techniques mentioned above to determine the optimum parameters for machining all the materials (i.e., steel and nanocomposite materials). This novel hybrid approach enabled the specification of the optimum combination of factors and levels in all experiments of the full factorial experimental design.

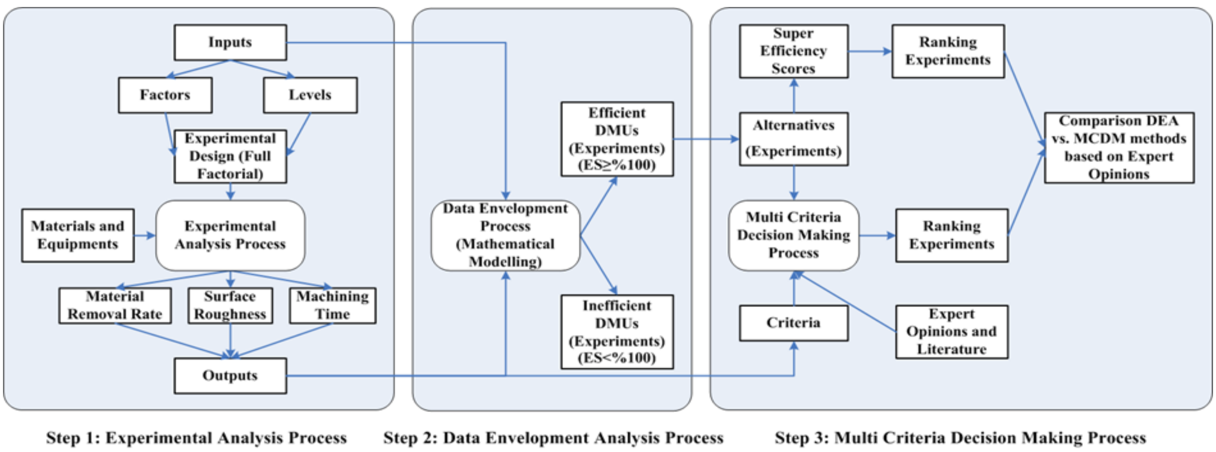
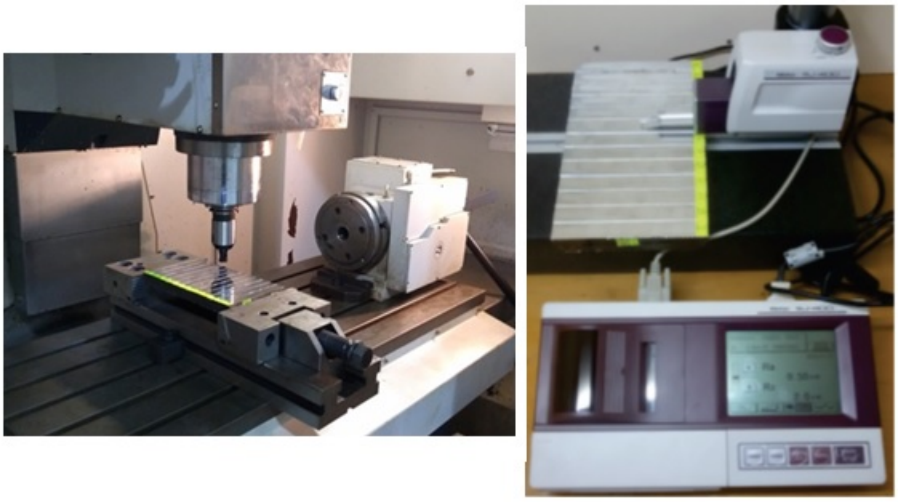


Figure 1. The structure of the proposed decision support system

STEP 1: EXPERIMENTAL ANALYSIS PROCESS

AISI 4140 steel used in the study is a material that is highly resistant to friction, impact, and cracking due to the intense carbon in its composition. Because of this feature, it is widely used in automobiles, aircraft, machine tools, and several machine parts (i.e., axles made for different purposes, shafts, and gears).

The material used in the experiments was cut to 260 x 150 x 25 mm using an aqueous saw and made suitable for the study. To eliminate the effects of oxides and residues on the surface of the part on the test results, the material was primarily subjected to surface milling. Cutting experiments were performed in the CNC vertical machining center of a SPINNER MVC1000 (refer Figure 2a). In the milling process, an R 390-11 T308M-PM 1030 PVD and TiAlN + TiN-coated carbide cutting tool, and an R 390-020B20-11M tool holder from Sandvik Inc. were also employed.



(a) (b)

Figure 2. a) The experimental setup, **b)** The portable device for measuring surface roughness

In the milling experiments, the cutting parameters and levels used in the milling of AISI 4140 steel were as follows: cutting speed (175, 250, and 325 m/min), feed rate (0.08, 0.12, and 0.16 mm/rev), depth of cut (0.5, 1, and 1.5 mm), and number of cutting tool inserts (1, 2, and 3 units).

In the experiments, the following were considered as outputs: material removal rate (Eq. 1), machining time (Eq. 2), and minimum–maximum values of the surface roughness. The surface roughness was measured using a MITUTOYO SJ-400 portable surface roughness tester (Figure 2b).

$$MRR = wdf_r \tag{1}$$

where *MRR* is material removal rate (mm^3/min), *w* is the width of the cut (mm), *d* is the depth of the cut (mm), and f_r is the feed rate (mm/min) (Groover, 2010).

$$T_m = \frac{L+A}{f_r} \tag{2}$$

where T_m is the machining time (min), L is the cut length (mm), and A is the approach distance (mm) (Groover, 2010).

STEP 2: DATA ENVELOPMENT ANALYSIS PROCESS

The second step was to determine the most efficient among all experiments using data envelopment analysis (DEA) method. The DEA method is effective in comparing decision making units in terms of relative effectiveness (Wen and Li, 2009). Liu and Chuang (2009) state that several situations in the use of the DEA method cause complexity and difficulty. For example, it is difficult to measure, or imprecise, the number of inputs or outputs. To obtain reliable DEA results, the exact values of the inputs and outputs should be obtained. However, obtaining exact numbers or values from numerous systems, processes, and experiments may be difficult. In this case, fuzzy environmental conditions become effective. We used the fuzzy DEA method because the output (i.e., surface roughness) had fuzzy numbers owing to the replication of the experiments. The efficiency scores of all experiments are listed in Table 1.

Table 1. Efficiency scores: E: Experiment

Experiments	Efficiency Scores (%)	Experiments	Efficiency Scores (%)	Experiments	Efficiency Scores (%)
E1	**100.00**	E66	99.87	E41	87.95
E2	**100.00**	E69	99.83	E14	87.03
E21	**100.00**	E51	99.65	E9	86.82
E27	**100.00**	E48	99.51	E33	86.63
E28	**100.00**	E43	99.49	E13	86.61
E32	**100.00**	E77	99.07	E42	86.46
E37	**100.00**	E74	99.06	E6	86.24
E54	**100.00**	E59	96.20	E30	85.38
E55	**100.00**	E35	96.04	E68	84.99
E56	**100.00**	E25	95.73	E15	84.86
E57	**100.00**	E4	95.47	E5	84.84
E58	**100.00**	E10	94.68	E38	84.68
E60	**100.00**	E67	94.39	E36	84.55
E61	**100.00**	E40	94.24	E46	84.36
E62	**100.00**	E16	92.04	E71	84.32
E63	**100.00**	E20	91.84	E52	83.71
E64	**100.00**	E3	91.31	E18	83.35
E70	**100.00**	E39	90.47	E53	82.73
E73	**100.00**	E12	90.16	E8	82.09
E75	**100.00**	E19	90.11	E49	80.92
E78	**100.00**	E11	89.98	E17	80.38
E79	**100.00**	E47	89.64	E34	79.87
E81	**100.00**	E29	89.60	E50	79.77
E72	99.99	E23	89.49	E26	79.20
E80	99.99	E7	89.45	E65	77.96
E24	99.95	E45	89.32	E31	76.08
E76	99.95	E22	88.20	E44	73.37

STEP 3: MULTI CRITERIA DECISION MAKING PROCESS

Step 3 includes the application of the expert opinion-based multi criteria decision making process, as shown in Figure 3. In this step, a fuzzy analytical hierarchy process was conducted to rank the efficient experiments, which were calculated in the previous step based on the opinions of a number of experts, consisting of mechanical and industrial engineers. The fuzzy AHP method is an extension of the AHP method developed by Saaty (1980). It combines the AHP method and fuzzy set theory (Duran and Aguilo, 2008). In the first stage, a hierarchy was constructed to solve the problem. The structure of this hierarchy is illustrated in Figure 3. In the second stage, a fuzzy comparison matrix is developed, and a fuzzy weight vector is established. Ayag and Ozdemir (2006) used triangular fuzzy numbers to develop a matrix.

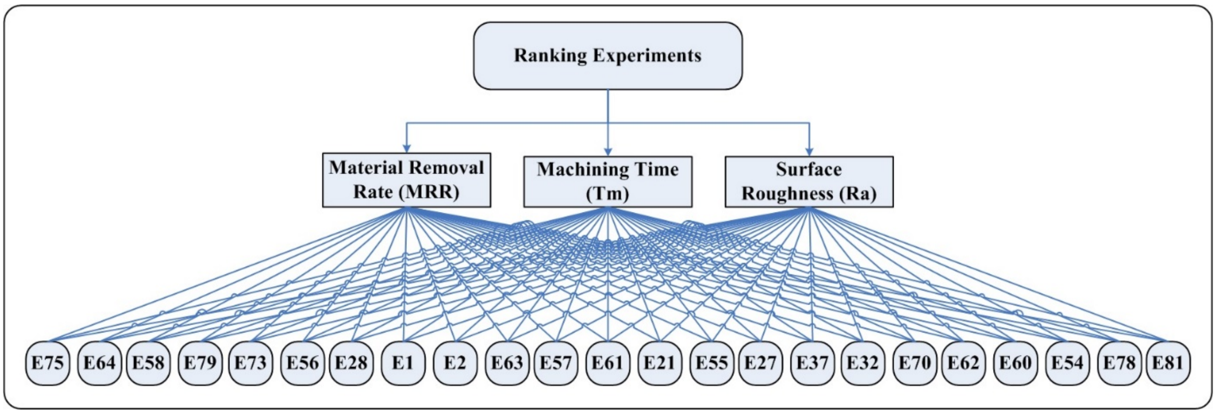


Figure 3. The structure of the MCDM problem

The fuzzy pairwise comparison matrix, fuzzy weights and normalized weights for the main criteria are listed in Table 2. Fedai et al. (2018) stated that the surface roughness is an important factor affecting the machinability of a material. This is a common problem encountered on surfaces after machining and it affects material quality. The material removal rate and machining time were the other factors affecting the quality that were considered in this study. From Eqs. (1) and (2), it is evident that the material removal rate and machining time are inversely proportional. However, surface roughness is more important than these two criteria in manufacturing materials with the desired quality. For these reasons, the criteria were weighted, as shown in Table 2. We also prepared a fuzzy pairwise comparison matrix for all criteria.

Table 2. Pairwise comparison matrix of the criteria

Response	MRR	Tm	Ra	Fuzzy Weights			Normalized Weights
MRR	1	$\tilde{1}$	$\widetilde{8^{-1}}$	0.089	0.093	0.097	0.100
Tm	$\widetilde{1^{-1}}$	1	$\widetilde{8^{-1}}$	0.089	0.093	0.097	0.100
Ra	$\tilde{8}$	$\tilde{8}$	1	0.681	0.745	0.805	0.800

In Table 3, the geometric means for all experiments after establishing the fuzzy comparison matrix, are presented. Subsequently, the fuzzy weights for each alternative are determined, and the fuzzy weights are averaged. Finally, a normalization procedure is performed. We applied the fuzzy AHP procedure to all criteria (i.e., MRR, Tm, and Ra).

Table 3. Geometric mean, fuzzy weights, and normalized weights for the first criterion (i.e., material removal rate)

Experiments	Geometric Mean			Fuzzy Weights			Average	Normalized Weights
E75	1.269	1.882	2.295	24.311	52.501	92.488	56.433	0.061134
E64	0.426	0.602	0.918	8.155	16.788	37.007	20.650	0.022370
E58	0.554	0.800	1.439	10.610	22.309	57.995	30.305	0.032829
E79	1.231	1.882	2.437	23.589	52.501	98.234	58.108	0.062948
E73	0.554	0.800	1.439	10.610	22.309	57.995	30.305	0.032829
E56	0.554	0.800	1.439	10.610	22.309	57.995	30.305	0.032829
E28	0.230	0.291	0.382	4.402	8.126	15.376	9.301	0.010076
E1	0.176	0.206	0.283	3.371	5.741	11.418	6.843	0.007413
E2	0.306	0.394	0.531	5.853	10.988	21.403	12.748	0.013810
E63	1.269	1.882	2.589	24.311	52.501	104.337	60.383	0.065413
E57	0.741	1.106	1.798	14.197	30.849	72.467	39.171	0.042433
E61	0.719	1.106	1.745	13.775	30.849	70.316	38.313	0.041504
E21	0.777	1.140	1.594	14.891	31.793	64.237	36.974	0.040053
E55	0.289	0.383	0.557	5.536	10.691	22.450	12.892	0.013966

E27	1.308	1.882	2.668	25.055	52.501	107.529	61.695	0.066834
E37	0.344	0.439	0.623	6.594	12.238	25.125	14.652	0.015872
E32	0.754	1.140	1.798	14.449	31.793	72.467	39.570	0.042865
E70	1.072	1.746	2.133	20.531	48.703	85.949	51.728	0.056036
E62	1.231	1.882	2.512	23.589	52.501	101.240	59.110	0.064033
E60	1.231	1.882	2.512	23.589	52.501	101.240	59.110	0.064033
E54	1.324	1.826	2.750	25.370	50.943	110.819	62.377	0.067573
E78	1.365	1.826	2.834	26.146	50.943	114.210	63.766	0.069078
E81	1.432	1.999	3.025	27.426	55.763	121.928	68.372	0.074067
Total	19.157	27.895	40.302				923.112	1.000000
Inverse	0.052	0.036	0.025					
Increasing Order	0.025	0.036	0.052					

In the fuzzy AHP methodology, consistency ratio of the matrix is calculated to control the results of the study and ensure that the comparison is acceptable, by using Eqs. (3) and (4) (Duran and Aguilo, 2008).

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{3}$$

where *CI* means consistency index and n represents the number of alternatives.

$$CR = {}^{CI}/_{RI} \tag{4}$$

where *CR* is the consistency ratio and *RI* is the random consistency index developed by Saaty (1980). Table 4 lists the consistency ratios of all fuzzy comparison matrices used in this study; all matrices are acceptable because the consistency ratios are less than 0.10.

Table 4. Consistency Ratios

Fuzzy Comparison Matrix	λ_{max}	**Consistency Index (CI)**	**Random Consistency Index (RI)**	**Consistency Ratio (CR)**
Main Criteria	3.000	0.0000	0.5800	0.0000
For MRR	23.304	0.0138	1.6526	0.0084
For Tm	23.312	0.0142	1.6526	0.0086
For Ra	23.333	0.0151	1.6526	0.0092

In the third step, ranking all alternatives and selection of the best alternative is performed. Table 5 presents the results of fuzzy DEA – fuzzy AHP along with the results from the fuzzy DEA with super efficiency.

RESULTS AND DISCUSSION

The cutting speed (m/min), feed rate (mm/rev), depth of cut (mm), and cutting tool inserts (units) were considered as factors. We selected the following three outputs that are widely preferred in the literature: surface roughness (μm), material removal rate (mm^3/min), and machining time (min).

In the second step, all 81 experiments were optimized using the fuzzy data envelopment analysis method based on the input–output relationship. Among them, 23 experiments (28%) were determined to be efficient, and all efficiency scores were between 73.37 and 100%. Using the super-efficiency method, these efficient experiments were ranked, and the super-efficiency scores were found to be between 100 and 130.88%. The parameters of the most efficient experiment are cutting speed - 325 m/min, feed rate - 0.16 mm/rev, depth of cut - 0.5 mm, and cutting tool inserts - 3 units. The cutting speed of the first six efficient experiments was 325 m/min, whereas the number of cutting tool inserts in two of the three experiments was one unit. The number of cutting tool inserts in the four experiments with the lowest efficiency score was three (refer Table 5).

Table 5. Comparison of the results from fuzzy DEA with super efficiency & fuzzy DEA-fuzzy AHP. A: cutting speed, B: feed rate, C: depth of cut, and D: cutting tool inserts

Fuzzy DEA with super efficiency			Fuzzy DEA – Fuzzy AHP		
Combinations	**Scores**	**Rank**	**Combinations**	**Scores**	**Rank**
(E75) $A_3B_3C_2D_3$	130.88%	1	(E64) $A_3B_2C_1D_1$	6.28%	1
(E64) $A_3B_2C_1D_1$	129.09%	2	(E73) $A_3B_3C_1D_1$	6.24%	2
(E58) $A_3B_1C_2D_1$	123.08%	3	(E58) $A_3B_1C_2D_1$	6.15%	3
(E79) $A_3B_3C_3D_1$	122.47%	4	(E61) $A_3B_1C_3D_1$	6.12%	4
(E73) $A_3B_3C_1D_1$	117.45%	5	(E28) $A_2B_1C_1D_1$	5.88%	5
(E56) $A_3B_1C_1D_2$	117.17%	6	(E55) $A_3B_1C_1D_1$	5.84%	6
(E28) $A_2B_1C_1D_1$	113.31%	7	(E56) $A_3B_1C_1D_2$	5.79%	7
(E1) $A_1B_1C_1D_1$	112.01%	8	(E79) $A_3B_3C_3D_1$	5.76%	8
(E2) $A_1B_1C_1D_2$	110.86%	9	(E70) $A_3B_2C_3D_1$	5.58%	9
(E63) $A_3B_1C_3D_3$	110.23%	10	(E37) $A_2B_2C_1D_1$	5.44%	10
(E57) $A_3B_1C_1D_3$	108.53%	11	(E32) $A_2B_1C_1D_2$	5.20%	11
(E61) $A_3B_1C_3D_1$	108.43%	12	(E62) $A_3B_1C_3D_2$	5.03%	12
(E21) $A_1B_3C_1D_3$	105.70%	13	(E1) $A_1B_1C_1D_1$	4.84%	13
(E55) $A_3B_1C_1D_1$	105.67%	14	(E2) $A_1B_1C_1D_2$	4.62%	14
(E27) $A_1B_3C_3D_3$	104.26%	15	(E63) $A_3B_1C_3D_3$	3.01%	15
(E37) $A_2B_2C_1D_1$	102.61%	16	(E60) $A_3B_1C_2D_3$	3.01%	16
(E32) $A_2B_1C_1D_2$	101.84%	17	(E57) $A_3B_1C_1D_3$	2.72%	17
(E70) $A_3B_2C_3D_1$	101.03%	18	(E81) $A_3B_3C_3D_3$	2.18%	18
(E62) $A_3B_1C_3D_2$	100.93%	19	(E78) $A_3B_3C_1D_3$	2.17%	19
(E60) $A_3B_1C_2D_3$	100.76%	20	(E54) $A_2B_3C_3D_3$	2.15%	20
(E54) $A_2B_3C_3D_3$	100.10%	21	(E75) $A_3B_3C_2D_3$	2.12%	21
(E78) $A_3B_3C_1D_3$	100.00%	22	(E27) $A_1B_3C_3D_3$	2.01%	22
(E81) $A_3B_3C_3D_3$	100.00%	23	(E21) $A_1B_3C_1D_3$	1.86%	23

In the third step, these 23 efficient experiments were optimized using the fuzzy analytical hierarchy process method. The most important advantage of this step is the establishment of fuzzy comparison matrices by an expert team, analyzing and interpreting the experimental results. Therefore, efficient experiments were compared in a fuzzy environment, based on expert opinions. The parameters of the most optimal experiment are as follows: cutting speed - 325 m/min, feed rate - 0.12 mm/rev, depth of cut - 0.5 mm and cutting tool inserts - 1 unit. The parameters of the last experiment are: cutting speed - 175 m/min, feed rate - 0.16 mm/rev, depth of cut - 0.5 mm, and cutting tool inserts - 3 units. One unit of the cutting tool insert was used, and the cutting speed was 325 m/min in eight of the first nine experiments. Number of cutting tool inserts for the last eight experiments is 3 units whereas the feed rate of the last six experiments is 0.16 mm/rev (refer Table 5).

In the literature, studies that focused on the optimization of machining parameters (i.e., Basar et al. (2018), Fedai et al. (2018), and Sarikaya et al. (2015)) stated that the minimum surface roughness value was obtained in experiments in which the cutting speed was the highest and the number of cutting tool inserts was one. The fuzzy DEA with the super-efficiency approach developed in the second step and the fuzzy DEA-fuzzy AHP approach that we proposed in the third step also produced results parallel to those in the literature.

In addition, the fuzzy DEA-fuzzy AHP approach provided a more efficient ranking than the fuzzy DEA with a super-efficiency approach. Based on the first ten experiments in Table 5, it was determined that the cutting speed was the highest in 70% of the experiments using the FDEA approach and in 80% of the experiments using the FDEA-FAHP approach. In addition, it was observed that the number of cutting tool inserts was one in 60% of the experiments using the FDEA approach and 90% of the experiments using the FDEA-FAHP approach. Moreover, the combination of experiments with both the highest cutting speed and one cutting tool insert was determined to be 40% of the experiments in the FDEA approach and 70% in the FDEA-FAHP approach. These results verify that the FDEA-FAHP approach proposed in this study produces a better ranking.

From Table 5, it can be observed that the results of the fuzzy DEA-fuzzy AHP approach and fuzzy DEA with super-efficiency clearly differ. The fuzzy DEA with super-efficiency determines efficiency within the framework of the input-output relationship and does not consider any expert opinion. In addition, none of the criteria had different weights. These situations can lead to failure in making robust and reliable decisions toward solving the problems examined. The problem that we analyzed was evaluated using criteria with different priorities. Based on expert opinions, surface roughness is more important in this problem because it affects the quality of the material (Fedai et al., 2018). Under these circumstances, assigning equal importance to all criteria will generate misleading results.

CONCLUSION

In this study, we developed a novel decision support system for optimizing machining parameters. To achieve this end, we integrate three distinct techniques: experimental design and analysis, fuzzy DEA, and fuzzy AHP. We also compared the results of the fuzzy DEA with those of super-efficiency and fuzzy DEA-fuzzy AHP. The results of the two approaches are clearly different based on the weights considered for the outputs, and the fuzzy DEA-fuzzy AHP approach outperforms the fuzzy DEA with the super-efficiency approach. Therefore, this study revealed the importance of expert opinion-based decision-making processes.

Numerous users, such as researchers studying machining, managerial teams, engineers working in industries, and decision-makers in research and development activities in this field, can employ this approach as a helpful decision support tool to determine optimum input parameters in their experimental studies. In addition, a more complex multi-response optimization can be performed by simultaneously considering more input parameters and levels. Thus, related decision makers allow managerial teams to obtain and facilitate a more efficient design of manufacturing processes, thus avoiding possible manufacturing defects. Moreover, the machinability of related materials can be improved by increasing the surface quality and reducing the cost and time. The results obtained in this study will provide industrialists processing AISI 4140 steel with more effective decision-making support for the selection of input and output parameters.

One of the limitations of this study is that only the fuzzy AHP methodology was used as an expert opinion-based MCDM technique and was combined with the fuzzy DEA approach. However, the AHP method has been integrated with other MCDM techniques (i.e., TOPSIS and PROMETHEE) in several studies to generate more accurate and reliable results. Another limitation is that the experiments were designed using only four factors and three levels, although many factors and levels have been used in the literature. Future work could include more factors and levels in the experimental analysis process (i.e., Step 1). A future research direction is to compare this approach with other MCDM techniques instead of using the AHP method. The criteria and alternatives were weighted using only the AHP method. Weighting can also be conducted using other methods such as entropy. Simultaneously, different output parameters such as the cutting tool temperature and cutting force can be considered.

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