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

DOI:10.36909/jer.13567

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ABSTRACT

The aim of this study is to develop a novel decision support system, which has never been developed yet, in order to optimize machining parameters. We combine the three distinct methods: experimental design and analysis, fuzzy data envelopment analysis (DEA) and fuzzy analytical hierarchy process (AHP). Firstly, a full factorial experiment including four factors and three levels is carried out. We take into account cutting speed, feed rate, depth of cut and number of cutting tool inserts as factors. The following three outputs are selected: Material Removal Rate, Machining Time and Surface Roughness. Secondly, a total of 23 experiments are determined as efficient decision-making units using fuzzy DEA with super efficiency method. Finally, a fuzzy AHP approach is conducted to rank the efficient experiments among each other. In conclusion, the results show that the Fuzzy DEA-Fuzzy AHP and the Fuzzy DEA with Super Efficiency generate clearly different rankings of experiments and Fuzzy DEA-Fuzzy AHP Approach has outperformed Fuzzy DEA with Super Efficiency Approach. The results highlight the importance of taking into account the expert opinions in the decision-making processes.

Key words: 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 many different industries, especially automotive and aerospace, since it has a variety of characteristic features, for example, weldability, good formability, and excellent corrosion resistance properties and high strength. In addition, machinery, parts and apparatus, agricultural vehicles, a number of products used in the defense areas and the petroleum and derivatives industry are various area of usage of AISI 4140 steel. Machining operations are performed on the material with various methods since it has a very wide area of use (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 affecting the productivity in manufacturing. In order to adapt to new technologies and survive in the competitive markets, the variables that affect these factors must be controlled. CNC milling is one of the traditional machining methods frequently used in the manufacturing and other industrial sectors. Many studies have concentrated on cutting parameters to improve the quality of machining processes in milling. The performance of the milling mainly depends on the selection of the most appropriate input parameters to optimize various objective functions, such as maximizing material removal rate (MRR), minimizing machining time (Tm) and surface roughness (Ra) (Kumar and Verma, 2020). Most of the deformation occurring between tools and materials during machining causes some difficulties to achieve the desired optimization goals due to the result of the interaction of many factors. In order 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).

There exist a number of studies on optimization of machining parameters in the literature. The studies are designed according to experimental design methods (i.e. Full factorial, Taguchi and so on) and then, main and interaction effects are analyzed, for example Fedai et al. (2018) and Kahraman et al. (2018). In general, single and multiple response optimization studies are conducted, for example Ananthakumar et al. (2019), Sharma et al. (2019) and Basar et al.

(2019). However, fuzzy environment has not been obviously taken into account. On the other hand, multiple replications are performed for each experiment in the studies. Thus, more than one values are generated for each output. In this case, it reveals that the study does not have exact values and has an average and standard deviation value. These circumstances suggest that such studies should use the fuzzy logic approach to overcome this type of uncertainties. In a number of studies, the optimum values of the input parameters are determined either by data envelopment analysis or by multi-criteria decision making methods (i.e. TOPSIS, PROMETHEE or AHP) using the inputs and outputs obtained from the experimental analysis, for example Manoj et al. (2018), Chakraborty et al. (2019), Phan and Muthuramalingam (2020), Naik et al. (2020) and Basar et al. (2020). In other studies, the criterion weights are calculated using AHP method and then, the weights are embedded into other multi-criteria decision making methods, for example Singaravel and Selvaraj (2015), Nadda et al. (2020) and Kumar and Verma (2020). However, our study differs from the literature due to the following aspects: 1) A total of 81 experiments were conducted with 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 outputs' different values obtained from the replications were taken into account, 3) Efficient experiments determined by the Fuzzy DEA approach were optimized by using the Fuzzy AHP method based on expert opinions. No study regarding the optimization of the machining parameters has applied such this approach. But this study fills this gap in the literature.

The remaining 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 greater details. Section 3 discusses the results and Section 4 concludes the study, respectively.

THE PROPOSED DECISION SUPPORT SYSTEM

In this study, we combined the following three methods to develop a decision support system (see Figure 1) in order to optimize machining parameters: Experimental design and analysis, fuzzy data envelopment analysis (DEA) and fuzzy analytical hierarchy process (AHP). Firstly, a full factorial experiment (3^4 =81) was designed. This experimental design consists of four factors (i.e. cutting speed, feed rate, depth of cut and number of cutting tool inserts) and three levels. Three output parameters (i.e. material removal rate, surface roughness and machining time) were measured. Secondly, all inputs and generated outputs in the experimental design and analysis were then fed into the fuzzy data envelopment analysis models. Thus, the efficient Decision Making Units (i.e. experiments) were determined. Finally, the efficient experiments were investigated in terms of multi criteria decision making problem to optimize multi-response problem and rank the alternatives by taking into account expert opinions. Thus, this decision support system is able to assess and compare the machining parameters in fuzzy environment. Briefly stated, the main contribution of the study is to develop a decision support system by integrating three distinct techniques mentioned above to determine optimum parameters in machining all materials (i.e. steels, nanocomposite materials). This novel hybrid approach enables to specify the optimum combination of factors and levels amongst all experiments of the full factorial experimental design.

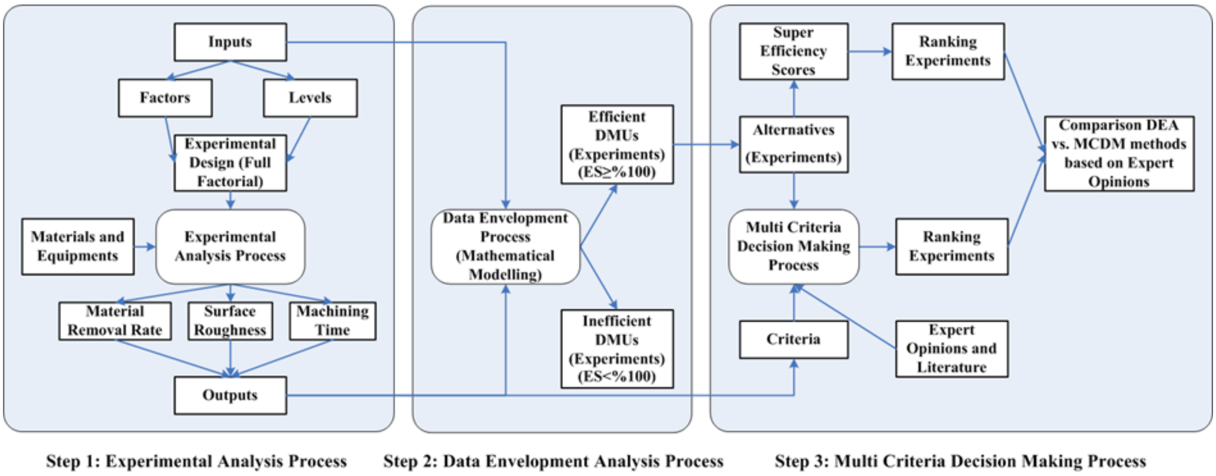
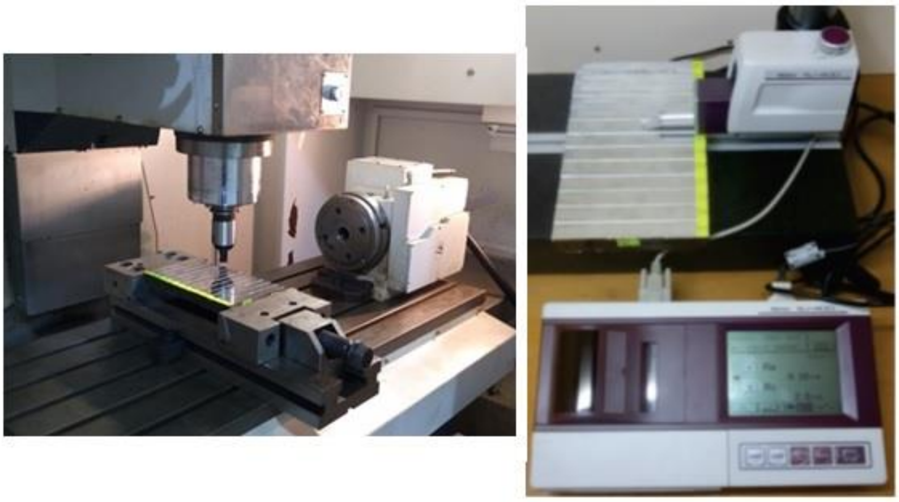


Figure 1 The structure of the proposed decision support system

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. Due to this feature, it has an intensive usage area in automotive, aircraft, machine tools and many machine parts (i.e. axles made for different purposes and shafts and gears).

The material used in the experiments was cut to 260x150x25 mm with an aqueous saw and made suitable for the study. In order to eliminate the effects of oxides and residues on the surface of the part on the test results, the material was primarily subjected to a surface milling process. Cutting experiments were carried out in CNC vertical machining center of SPINNER MVC1000 (see Fig. 2a). In the milling process, R 390-11 T308M-PM 1030 PVD and TiAlN + TiN coated carbide cutting tool and R 390-020B20-11M tool holder from Sandvik Inc. were also used.



(a) (b)

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

In milling experiments, cutting parameters and levels used in the milling of the AISI 4140 steel are 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 followings were considered as outputs, i.e. Material Removal Rate (see Eq. 1 for the formula), Machining Time (see Eq. 2 for the formula) and Minimum-Maximum values of Surface Roughness. Surface roughness was measured with the MITUTOYO SJ-400 portable surface roughness device (see Fig. 2b).

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

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

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

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

STEP 2: DATA ENVELOPMENT ANALYSIS PROCESS

Our second step is to determine the efficient experiments amongst all experiments and to do this, we used data envelopment analysis (DEA) method. DEA method is an effective method of comparing decision making units in terms of relative effectiveness (Wen and Li, 2009). Liu and Chuang (2009) states a number of situations in the use of DEA method cause complexity and difficulty. For example, difficulties in measuring or imprecise numbers of inputs or outputs. If desired to get reliable results from DEA, the exact values of inputs and outputs should be obtained. However, obtaining exact numbers or values from a number of systems, processes or experiments might be very difficult. In this case, fuzzy environment conditions come into play. We have used fuzzy DEA method due to that the output (i.e. surface roughness) has the fuzzy numbers because of the replications of experiments. The efficiency scores of the all experiments are given 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

The Step 3 in our study includes the application of the expert opinion-based multi criteria decision making process as seen in Figure 3. At this Step, fuzzy analytical hierarchy process was carried out 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. Fuzzy AHP method is an extension version of Analytical Hierarchy Process method developed by Saaty (1980). It consists of the combination of AHP method and the fuzzy set theory (Duran and Aguilo, 2008). In the first stage, construction of hierarchy for the solution of the problem. Our structure of the hierarchy is presented in Figure 3. In the second stage, the fuzzy comparison matrix is developed, and fuzzy weight vector is established. Ayag and Ozdemir (2006) states that the triangular fuzzy numbers are used to develop the matrix.

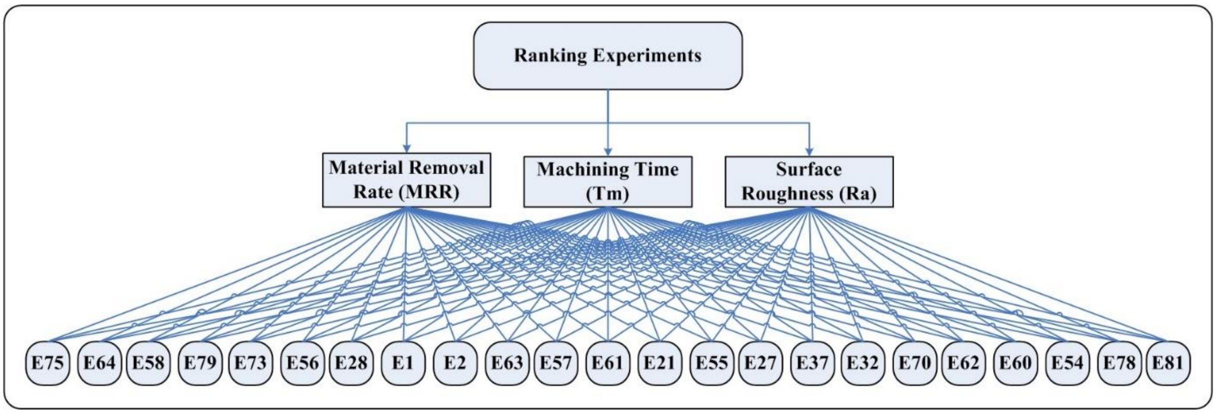


Figure 3 The structure of the MCDM problem

The fuzzy pairwise comparison matrix, fuzzy weights and normalized weights for the main criteria are given as an example in Table 2. Fedai et al. (2018) stated surface roughness is an important factor affecting the machinability of a material. It is also one of the common problems encountered on surfaces after machining. Therefore, it affects the quality of the material. Other factors affecting the quality used in this study are material removal rate and machining time. It can be understood from Eq. (1) and (2) that they are related and inversely proportional to each other. However, the surface roughness is very important than these two criteria in terms of manufacturing material with the desired quality. Due to these reasons, the criteria are weighted as in Table 2. We also prepared the fuzzy pairwise comparison matrix for the 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, we calculated geometric means for all experiments after the establishment of fuzzy comparison matrix. After that, fuzzy weights for each alternative are determined and then, we averaged the fuzzy weights. Finally, the normalization procedure was carried out. We applied the procedure of fuzzy AHP for 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 make sure whether the comparison is acceptable or not, by using Eq. (3) and (4) (Duran and Aguilo, 2008).

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

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

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

where *CR* means consistency ratio and *RI* is random consistency index and developed by Saaty (1980). Table 4 shows the consistency ratios of all fuzzy comparison matrices in this study and therefore, all matrices are acceptable due to that 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. Table 5 gives the results of Fuzzy DEA – Fuzzy AHP along with the results from the Fuzzy DEA with Super Efficiency.

RESULTS AND DISCUSSION

We used Cutting Speed (m/min), Feed Rate (mm/rev), Depth of cut (mm) and Cutting Tool Inserts (unit) as factor. We selected the following three outputs which have been widely preferred in the literature: Surface roughness (µm), material removal rate (mm^3/min) and machining time (min).

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 second step of our study, all of 81 experiments were optimized using fuzzy data envelopment analysis method on the basis of input-output relationship. 23 of these experiments (i.e. 28%) were determined to be efficient experiments and all efficiency scores were between 73.37% and 100.00%. Then, using the super efficiency method, these efficient experiments were ranked among themselves and the super efficiency scores were calculated to be between 100.00% and 130.88%. The parameters of the most efficient experiment are Cutting Speed with 325 m/min, Feed Rate with 0.16 mm/rev, Depth of cut with 0.5 mm and 3 units of Cutting Tool Inserts. The cutting speed of the first six efficient experiments is 325 m/min whereas the number of cutting tool inserts of two out of three of these experiments is 1 unit. Number of cutting tool inserts of 4 experiments which has the lowest efficiency score is 3 units (see Table 5).

In the third step of our study, these 23 efficient experiments were optimized by the fuzzy analytical hierarchy process method. The most important advantage of this step is the establishment of fuzzy comparison matrices by analysing and interpreting the experimental results by an expert team. Thus, the efficient experiments were compared based on expert opinion with each other in a fuzzy environment. The parameters of the most optimal experiment are as follows: Cutting Speed with 325 m/min, Feed Rate with 0.12 mm/rev, Depth of cut with 0.5 mm and 1 unit of Cutting Tool Inserts. The parameters of the last experiment are: Cutting Speed with 175 m/min, Feed Rate with 0.16 mm/rev, Depth of cut with 0.5 mm and 3 units of Cutting Tool Inserts. 1 unit Cutting Tool Inserts was used whereas Cutting Speed was 325 m/min in the 8 of the first 9 experiments. Number of Cutting Tool

Inserts for the last eight experiments is 3 units while the Feed Rate of the last six experiments is 0.16 mm/rev (see Table 5).

In the literature, the studies that have been interested in the optimization of machining parameters (i.e. Basar et al. (2018), Fedai et al. (2018) and Sarikaya et al. (2015)) stated the minimum surface roughness value is obtained in the experiments which the cutting speed is the highest and the number of cutting tool inserts is 1. The Fuzzy DEA with Super Efficiency Approach developed in the second step of our study and the Fuzzy DEA-Fuzzy AHP Approach that we proposed in the third step also produced the results parallel to these results from the literature.

In addition, the Fuzzy DEA-Fuzzy AHP approach has made a more efficient ranking compared to the Fuzzy DEA with Super Efficiency Approach. Having a look at the first ten experiments in Table 5, it has been determined that the cutting speed is the highest in 70% of the experiments in the FDEA approach and in 80% of the experiments in the FDEA-FAHP approach. In addition, it is observed that the number of cutting tools is 1 in 60% of the experiments in the FDEA approach and 90% of the experiments in the FDEA-FAHP approach. Moreover, the combination of experiments with both the highest cutting speed and 1 cutting tool insert is determined to be 40% of the experiments in the FDEA approach and 70% in the FDEA-FAHP approach. All of these results show that the FDEA-FAHP approach we proposed in this study produces a better ranking.

According to Table 5, the results of Fuzzy DEA-Fuzzy AHP Approach and Fuzzy DEA with Super Efficiency clearly differ. The Fuzzy DEA with Super Efficiency determines the efficiency within the framework of input-output relationship and does not take into account any expert opinion. Also, neither criterion has a different weight. These situations can lead that we fail to make robust and reliable decisions in solving the problems we examine. At this point, the problem we are working on is evaluated by criteria with different priorities. Based on expert opinion, surface roughness is more important in this problem due to that it affects the quality of material (Fedai et al., 2018). Under these circumstances, giving equal importance to all criteria will allow misleading results to be produced as a result of the study.

CONCLUSION

In this study, we have developed a novel decision support system for optimizing the machining parameters. To do this, we have integrated three distinct techniques, i.e., experimental design and analysis, fuzzy DEA and fuzzy AHP methods. We have also compared the results of Fuzzy DEA with Super Efficiency and Fuzzy DEA-Fuzzy AHP. The results of two approach are clearly different based on the weights considered for the outputs and Fuzzy DEA-Fuzzy AHP Approach has outperformed Fuzzy DEA with Super Efficiency Approach. Therefore, this study has revealed the importance of expert opinions-based decision making process.

A number of users such as researchers studying on machining, managerial teams and engineers working in the industrial companies and decision makers in the research and development activities in this field can use this approach as a helpful decision support tool to determine optimum input parameters in theirs experimental studies. In addition, a more complex multi-response optimization will be able to carry out by considering more input parameters and levels at the same time. Thus, the related decision makers allow the managerial teams can obtain and facilitate the more efficient design of the manufacturing processes, and possible manufacturing defects can be avoided. Moreover, the machineability of the related materials will be able to improve by increasing the surface quality and reducing cost and time. The results obtained from this study will provide industrialists processing AISI 4140 steel with a more effective decision-making support in the selection of input and output parameters.

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

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