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A Novel Hybrid Multi Criteria Decision Making Model: Application to Turning Operations

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Abstract: Multi criteria decision making models (MCDM) are extensively used in material and process selection in engineering. In this study, a novel hybrid decision making model is developed. Best-Worst method (BWM) is hybridized with TOPSIS, Grey Relational Analysis (GRA) and Weighted Sum Approach (WSA). Developed hybrid models produce similar results in different weight value of decision makers so they are combined. The model is tested in a turning operation and an optimization study is conducted by using Taguchi experimental design. The developed model can be used by engineers and operators in manufacturing environment.

Keywords: *Multi criteria decision making, Best-Worst method, Taguchi Method, Optimization, Turning operation*

1. Introduction

The main factor of manufacturing is to shape metals as machining and non-machining forms. In machining methods, machines are operated for a long time, production parameters are adjusted easily and the quality of surface is obtained in desired levels, so these machining methods will outperform the other manufacturing methods. It is very important to choose the production parameters in machining operations. If the production parameters aren't chosen properly, excessive tool wear is observed and the surface quality decreases. After appropriate dimensions and tolerances are obtained, obtaining a satisfactory quality of surface is important. The surface quality is affected by workpieces, tools, machines and machining conditions. Surface quality affects mechanical life of components. Therefore, the prediction of surface roughness is required. The chatter vibrations are effective in the prediction of surface roughness. The chatter vibrations are the ones which are formed with a self-excited mechanism between workpieces and tools. A wavy surface is observed on the workpiece due to both previous cycle and the structural vibrations in the turning. While the system is vibrated with chatter frequency which is very close to the structural mode, the maximum chip thickness may increase exponentially by depending on the phase shift between two consecutive waves. The growth of variable chip thickness increases the cutting forces by increasing the vibrations, and leads to the wavy surface on the workpiece. Stable cutting depths are the cutting depths where the chatter vibrations are not observed during machining [1].

In recent years, there has been an increasing amount of literature on MCDM. When the studies in literature are investigated, MCDM techniques are grouped under 15 topics: Energy-environment-sustainability, supply chain management, material, quality management, Geographic Information Systems (GIS), construction and project management, safety and risk management, manufacturing systems, technology management, operation research and soft computing, strategic management, knowledge management, production management, tourism management and the other fields [2]. For MCDM techniques, there are a lot of studies in the area of material science [3-8], production technologies [9], mass production [10], infrastructures [11], manufacturing systems [12], global production [13] and production strategies [14].

There is a large volume of published studies in MCDM for manufacturing and material science. Buyurgan and Saygın [15] studied part routing and real time scheduling using MCDM methods. For machine selection problem, İç et al. [16] used AHP method and Yurdakul and İç [17] developed TOPSIS model. Numerous studies have attempted to analyse material selection problem using TOPSIS, ELECTRE, PROMETHEE, VIKOR etc. [3,5,7,18-22]. Yurdakul [23] and Çalışkan et al. [24] analysed cutting tool selection problem via AHP, ANP, TOPSIS, VIKOR and EXPROM-2.

Different methods are developed for criteria weighting such as subjective and objective weighting. AHP is popular in subjective weighting of criteria but there are some drawbacks. Subjective scores generally lead to inconsistency during criteria weighting. During criteria weighting calculations, high inconsistency is observed in AHP, especially when the number of criteria increases. Therefore, researchers lead to new methods. One of the new methods developed in recent years is Best-Worst method [25]. This method provides to score only best-worst criteria vs. the other criteria. Therefore, pairwise calculations are easy. Furthermore, it is more consistent than AHP method.

Up to now, for MCDM techniques, previous studies are generally carried out in Operation Research-Soft Computing and energy-environment-sustainability. In machining operations, researchers rarely developed MCDM models. A few studies were observed in machining operations and chatter vibrations by using MCDM. Furthermore, developed model in this study is a new hybrid decision making model and it is used for the first time in the literature. Using proposed model, chatter free machining in turning operation could be performed.

In this study, Best-Worst method is combined with TOPSIS, GRA and WSA. The proposed model is tested in a turning operation. The criteria weights are calculated using Best-Worst

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Method. Using these criteria weights, the experiments which are designed by Taguchi method are ranked by using TOPSIS, GRA and WSA. Spearman correlation is used to determine the order of rankings.Because the order of rankings are nearly same, the average scores of three methods are taken into consideration, regression study is performed and an optimization model is developed. The study is validated experimentally.

In the second section, methodology is presented. In the third part, numerical study is explained with the results. Then, conclusion section is given.

2. Methodology

2.1. Experimental Design and Taguchi Method

Experimental design is used for decreasing the number of experiments and designing the experiments properly. It was firstly developed by the British statistician R.A. Fisher and others in 1920. The methods used in the statistical experimental design are classified into three classes as full factorial, fractional factorial and Taguchi methods [26].

Taguchi design is an optimization method which is based on parameter, system and tolerance design. The orthogonal arrays are used in order to show different experimental conditions. Different factors are tested in the minimum number with the orthogonal array Frequently, L4, L8 and L16 arrays are used for 2 levels and the L9 and L27 arrays are used for three levels [26].

2.2.Best-Worst Method (BWM)

Best-worst method is one of the new methods used in the determination of criteria weights [25]. When the method is compared with AHP, it outperforms as the pairwise comparison isn't performed between all criteria and consistency is high The calculation is performed using the following steps.

Step 1: Determination of decision-making criteria (c_1, c_2.....c_n).

Step 2: Determination of the best and the worst criteria.

Step 3: Scoring of the best criterion between 1-9 with the other criteria

$a_{Bj}=(a_{B1}, a_{B2},\dots a_{Bn})$.

a_{Bj}: comparison scores of the best criterion B with j th criteria.

Step 4: Scoring of the other criteria between 1-9 with the worst criterion

$a_{jw}=(a_{1w}, a_{2w}\dots a_{nw})^T$.

a_{jw}: The comparison scores of the worst criterion with j. criteria.

Step 5: Calculation of optimum weights (w_1*, w_2*, w_3* …… w_n*) and index for consistency ratio (ϵ*)

Best-Worst Method model is given below (Eq.1-4).

Min ϵ

subject to

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \epsilon \qquad (1)$$

$$\left|\frac{w_j}{w_W} - a_{jw}\right| \leq \epsilon \qquad (2)$$

$$\sum_j w_j = 1 \qquad (3)$$

$$w_j \geq 0 \qquad (4)$$

Consistency index table is given in Table 1 and consistency ratio is given in Eq.5.

$$\text{Consistencyratio} = \frac{\epsilon^*}{\text{consistencyindex}} \qquad (5)$$

Table 1. Consistency index table

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency index	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

2.3. Weighted Sum Approach (WSA)

Weighted sum model is one of the multi-criteria decision-making methods which is known at most in the decision-making theory. If all criteria are assumed as benefit criteria, higher values show better results. a_{ij} shows the performance value of A_i th alternative according to jth criteria and w_j defines the weights of jth criteria. Total of importance point of Ai th alternative is calculated by using Eq.6 [27]:

$$A_i = \sum_{j=1}^{n} w_j\, a_{ij} i = 1,2,3 \dots m \qquad (6)$$

Where,

m is the number of alternatives.

n is the number of criteria.

2.4. TOPSIS Algorithm

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) was developed by Yoon and Hwang in 1980. The steps of TOPSIS algorithm are given below [28]:

2.4.1. Decision matrix

While the evaluation criteria are in the columns of decision-making matrix, decision-making points are in the rows. The decision-making matrix is given in Eq.7:

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ . & & & . \\ . & & & . \\ . & & & . \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \qquad (7)$$

In A_{ij} matrix, the number of decision-making points is given as m and the number of evaluation factor is given as n. a_{ij} elements show the values of ith decision-making points according to the jth evaluation criteria.

2.4.2. Standard decision matrix

Standard decision-making matrix is calculated by using the decision-making matrix in Eq.8. This formula shows vector normalisation.r_{ij}shows normalised values of vector normalization.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}} \qquad (8)$$

Standard decision-making matrix is provided as follows (Eq.9):

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ . & & & . \\ . & & & . \\ . & & & . \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \qquad (9)$$

R_{ij} represents normalised matrix.In this stage, different normalization techniques can be used.

2.4.3. Weighted decision matrix

In this stage, standard decision-making matrix is multiplied by the weights (w_j) and weighted decision-making matrix (V_{ij}) is calculated (Eq. 10).

$$V_{ij} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ . & & & . \\ . & & & . \\ . & & & . \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \quad (10)$$

2.4.4. Ideal and negative ideal solutions

The highest value of weighted evaluating factors in the weighted decision-making matrix is chosen (the lowest one is chosen if the purpose is minimization). The ideal solution set is calculated by using Eq. 11.

$$A^* = \left\{ (\max_i v_{ij} \left| j \in J), (\min_i v_{ij} \right| j \in J') \right\} \quad (11)$$

The ideal solution set to be achieved is shown as:

$$A^* = \left\{ v_1^*, v_2^*, \ldots, v_n^* \right\}$$

The negative ideal solution set is determined by choosing the lowest ones of weighted evaluating factors in the weighted decision-making matrix (if the purpose is minimization, the highest one is chosen). The negative ideal solution set is calculated by the following equation (Eq. 12):

$$A^- = \left\{ (\min_i v_{ij} \left| j \in J), (\max_i v_{ij} \right| j \in J') \right\} \quad (12)$$

The negative ideal solution set is shown as:

$$A^- = \left\{ v_1^-, v_2^-, \ldots, v_n^- \right\}$$

J shows maximized cluster and J' shows minimized cluster.

2.4.5. Distinction measure

The deviations of the values of evaluating factors for each decision-making point from the solution sets are calculated by using the Euclidean distance approach. These deviations are called as distinction measures. The calculation of ideal distinction (S_i^*) measure is shown in Eq. 13 and the calculation of negative ideal distinction measure (S_i^-) is shown in Eq. 14.

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2} \quad (13)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad (14)$$

2.4.6. Proximity values relative to ideal solution

Ideal and negative ideal distinction measures are used while determining the proximity values according to the ideal solution. This value (Ci*) is the rate of negative ideal distinction measure in the total distinction measure. It is calculated by using following equation (Eq. 15):

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*} \quad (15)$$

C_i^* values are between 0 and 1 and they show alternative points. The higher values show that the alternative is better than the others.

2.5. Grey Relational Analysis (GRA)

This method consists of five steps [29].

1. Preparation of data set
2. Determination of reference series.
3. Normalisation of data matrix.
4. Calculation of grey relational coefficient.
5. Determination of grey relational degree.

In Grey Relational Analysis, $a_i$shows alternatives and $a_i(k)$shows criteria. They are displayed in Eq. 16-17.

$$a_i = (a_i(1), a_i(2), a_i(3), \ldots, a_i(k)) \quad (16)$$

$$k = 1,2,3, \ldots, n and i = 1,2,3, \ldots, m \quad (17)$$

Where, m shows the number of alternatives and n shows the number of criteria.

In Eq. 18 matrix of alternatives is given.

$$A = \begin{bmatrix} a_1(1) & \ldots & a_1(n) \\ \vdots & \ldots & \vdots \\ a_m(1) & \ldots & a_m(n) \end{bmatrix} \quad (18)$$

Observation values are given in decision matrix (A). A new series is obtained by using decision matrix. The new series is created by using the best values of each criteria of decision matrix. This series is called as reference series. Reference series is given in Eq. 19 and it is shown in matrix (Eq.20).

$$a_0 = (a_0(1), a_0(2), a_0(3), \ldots, a_0(n)) \quad (19)$$

$$A_{new} = \begin{bmatrix} a_0(1) & \cdots & a_0(n) \\ \vdots & \ddots & \vdots \\ a_m(1) & \cdots & a_m(n) \end{bmatrix} \quad (20)$$

Criteria matrix is normalized in order to become independent of the measurement unit. Grey relational coefficients are calculated after normalisation. After normalisation of criteria values, grey relational coefficients are calculated. Grey relational coefficient is used to determine how close $a_i(k)$and $a_0(k)$. Calculation of grey relational coefficient is given in Eq. 21-22.

$$\gamma(a_0(k), a_i(k)) = \frac{\Delta_{min} + \delta\Delta_{max}}{\Delta_{0i}(k) + \delta\Delta_{max}} \quad (21)$$

$$k = 1,2,3, \ldots, n and i = 1,2,3, \ldots, m \quad (22)$$

Where,

$\Delta_{0i}(k) = |a_0(k) - a_i(k)|$

$\Delta_{min} = \min_{\forall i} min_{\forall k} \{\Delta_{0i}(k)\}$

$\Delta_{max} = \max_{\forall i} max_{\forall k} \{\Delta_{0i}(k)\}$

$\delta$is the distinguishing coefficient and $\delta \in [0,1]$

Grey relational degree ($r(x_0, x_i)$) is determined after the calculation of grey relational coefficients. The formula of grey relational degree is obtained by using the average value of grey relational coefficients of each alternative. It is given in Eq. 23.

$$r(x_0, x_i) = \frac{1}{n} \sum_{k=1}^{n} \gamma(a_0(k), a_i(k)) \quad (23)$$

Where,

$r(x_0, x_i)$shows the grey relational degree between $a_i$and a_0.

2.6. Correlation Analysis

Correlation analysis measures the degree of correlation between two variables. Using scatter diagram, the relation between the variables is observed. Therefore, the value and direction of the relation between variables are determined [30].

2.6.1. Pearson correlation coefficient

Pearson correlation coefficient determines the linear relation between variables. It is represented with the symbol ‘r’ and is indicated by the following formula (Eq.24). In Eq. 24, x and y are the observation values of variables, $\bar{x}$and $\bar{y}$are the mean values of observations.

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y_i})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y_i})^2}} \quad (24)$$

2.6.2. Spearman correlation coefficient

Spearman correlation coefficient (rs) is used instead of Pearson correlation coefficient if there are any of the following assumptions which are given below. [30]:

-One of the variables is categorical.

-Both two variables distributed normally.

-The number of sample size is small.

-The relation between two variables is nonlinear.

The equation of Spearman correlation coefficient is given below (Eq.25)

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \quad (25)$$

Where,

$$d_i = rn(x_i) - rn(y_i)$$

n: the total number of observation values of two variables

d_i:the difference between sequence numbers.

3. Numerical Study

Best-Worst method (BWM) is combined with TOPSIS, Grey Relational Analysis (GRA) and Weighted Sum Approach (WSA). An optimization study is conducted using Taguchi experimental design. Then, regression study is performed

Gök’s study [31] is used for experimental study to test developed model. The chatter frequency occurred in the experiments is determined by recording the sound with a microphone and processing using LABVIEW 7.1 software. The cutting depth is increased slowly until the chatter vibration occurs. When the chatter vibration is occurred, the sound is recorded using a microphone. The cutting process is conducted for different tool overhang lengths (70-110 mm), the number of revolutions (125-710 rpm) and materials (AISI-1010, AISI-1050, Al-7075). Detailed explanations are given in the study [31].

3.1. Determination of Relative Weights of Parameters using BWM

Workpiece hardness, the number of revolution and tool overhang length are weighted by three experts who have experience in this topic (Table 2). In addition, consistency index and ratios are calculated for three different weighting ratios. According to the experts, workpiece hardness is more effective compared to the other cutting parameters. Also, the effect of tool overhang length is low. Weights are consistent because consistency ratios are lower than 0.1.

Table 2. Weights of cutting parameters (%)

Experts	W.hardness	The number of revolutions	Tool overhang length	C. index	C. ratio
E-1	64	28	8	0.32	0.07
E-2	52	42	7	0.24	0.05
E-3	59	34	7	0.26	0.06

In Table 3, the levels of parameters for experimental design are displayed. The number of revolutions, tool overhang length and workpiece hardness have 6, 3 and 3 levels respectively.

Table 3. The levels of parameters

Levels	The number of revolutions (rpm)	Tool overhang length (mm)	Workpiece hardness (HV)
1	125	70	124 (1st material)
2	180	90	165 (2nd material)
3	250	110	387.5 (3rd
4	355		
5	500		
6	710		

In Table 4, Taguchi experimental design (L18) is given. At this stage, the weights in Table 2, the levels of parameters in Table 3-4 and Taguchi experimental design are used to develop three hybrid decision making models. These models are BWM-WSA, BWM- TOPSIS, and BWM- GRA models.

Table 4. Experimental design (L18 Taguchi design)

Experiment no	The number of revolutions	Tool overhang length	Workpiece hardness
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	1
5	2	2	2
6	2	3	3
7	3	1	2
8	3	2	3
9	3	3	1
10	4	1	3
11	4	2	1
12	4	3	2
13	5	1	2
14	5	2	3
15	5	3	1
16	6	1	3
17	6	2	1
18	6	3	2

Normalisation matrix is calculated using the levels in Table 3 and experimental design in Table 4. The matrix is given in Table 5.

Table 5. Normalisation matrix

Experiment no	The number of revolutions	Tool overhang length	Workpiece hardness
1	1.000	1.000	1.000
2	1.000	0.500	0.844
3	1.000	0.000	0.000
4	0.906	1.000	1.000
5	0.906	0.500	0.844
6	0.906	0.000	0.000
7	0.786	1.000	0.844
8	0.786	0.500	0.000
9	0.786	0.000	1.000
10	0.607	1.000	0.000
11	0.607	0.500	1.000
12	0.607	0.000	0.844
13	0.359	1.000	0.844
14	0.359	0.500	0.000
15	0.359	0.000	1.000
16	0.000	1.000	0.000
17	0.000	0.500	1.000
18	0.000	0.000	0.844

3.2. BMW-WSA Hybrid Method

In Table 6, the results of BWM- WSA method for three different weights from Table 2 are presented. When the scores and rankings are examined, it is obtained that the first experiment is the best, whereas 18th try is the worst.

Table 6. Sensitivity analysis of BWM- WSA hybrid method for three different weights

Scores for weight-1	Ranking	Scores for weight-2	Ranking	Scores for weight-3	Ranking
1.000	1	1.000	1	1.000	1
0.940	4	0.961	4	0.945	4
0.851	7	0.902	7	0.863	7
0.848	2	0.769	10	0.819	2
0.787	5	0.729	2	0.764	5
0.668	10	0.726	13	0.698	10
0.643	8	0.691	5	0.634	8
0.640	3	0.582	8	0.611	13
0.608	11	0.579	11	0.598	11
0.583	9	0.520	16	0.590	3
0.580	6	0.410	3	0.535	6
0.577	13	0.407	14	0.534	9
0.456	12	0.392	9	0.417	12
0.370	14	0.371	6	0.382	14
0.310	15	0.330	17	0.340	16
0.280	16	0.308	12	0.282	15
0.220	17	0.217	15	0.240	17
0.068	18	0.059	18	0.059	18

3.3. BMW-TOPSIS Hybrid Method

In Table 7, the results of BWM- TOPSIS method for three different weights are presented. It is observed that the first try is the best, whereas 18th try is the worst.

Table 7. Sensitivity analysis of BWM- TOPSIS hybrid method for three different weights

Scores for weight-1	Ranking	Scores for weight-2	Ranking	Scores for weight-3	Ranking
1.000	1	1.000	1	1.000	1
0.915	4	0.943	4	0.920	4
0.824	2	0.874	7	0.820	7
0.809	7	0.766	10	0.784	2
0.797	5	0.674	13	0.759	5
0.712	8	0.653	2	0.689	8
0.687	3	0.635	5	0.671	10
0.661	6	0.594	8	0.630	3
0.645	10	0.556	16	0.603	6
0.621	9	0.545	11	0.583	11
0.594	11	0.443	14	0.564	9
0.511	12	0.439	3	0.517	13
0.473	13	0.414	6	0.468	12
0.379	14	0.385	9	0.392	14
0.329	15	0.357	17	0.364	16
0.303	16	0.320	12	0.305	15
0.198	17	0.219	15	0.230	17
0.088	18	0.082	18	0.080	18

3.4. BMW-GRA Hybrid Method

In Table 8, the results of BWM- GRA method for three different weights are presented. The results show that the first experiment is the best, whereas 18th experiment is the worst.

Table 8. Sensitivity analysis of BWM- GRA hybrid method for three different weights

Scores for weight-1	Ranking	Scores for weight-2	Ranking	Scores for weight-3	Ranking
1.000	1	1.000	1	1.000	1
0.899	4	0.935	4	0.907	4
0.841	2	0.861	7	0.813	2
0.789	7	0.773	10	0.807	7
0.760	3	0.753	13	0.727	3
0.740	5	0.723	2	0.720	5
0.665	10	0.680	16	0.694	10
0.659	6	0.658	5	0.652	13
0.622	9	0.607	3	0.633	6
0.621	13	0.571	8	0.607	8
0.615	8	0.560	11	0.597	9
0.578	11	0.542	6	0.570	11
0.520	16	0.531	9	0.560	16
0.513	12	0.467	17	0.497	12
0.454	15	0.463	14	0.452	14
0.447	14	0.456	12	0.442	15
0.433	17	0.423	15	0.437	17
0.368	18	0.363	18	0.363	18

In Table 9, correlation coefficients are presented according to three hybrid models with three different weights. When correlation coefficients and significance values are examined, it is observed that they are mostly consistent at 5% significance level.

Table 9. Spearman test for three hybrid decision making approach (H1-BMW-WSA,H2-BMW-TOPSIS, H3-BMW,GRA, W1-Weight 1, W2-Weight 2, W3-Weight 3)

	S.rho	H1 W-1	H1 W-2	H1 W-3	H2 W-1	H2 W-2	H2 W-3	H3 W-1	H3 W-2	H3 W-3
H1 W-1	Coef.	1.00	.719	.841	.880	.480	.950	.851	.548	.748
	Sig.	.	.001	.000	.000	.044	.000	.000	.019	.000
H1 W-2	Coef.	.719	1.00	.581	.692	.430	.668	.719	.218	.598
	Sig.	.001	.	.011	.001	.075	.002	.001	.385	.009
H1 W-3	Coef.	.841	.581	1.00	.792	.494	.771	.725	.507	.825
	Sig.	.000	.011	.	.000	.037	.000	.001	.032	.000
H2 W-1	Coef.	.880	.692	.792	1.00	.618	.860	.891	.550	.847
	Sig.	.000	.001	.000	.	.006	.000	.000	.018	.000
H2 W-2	Coef.	.480	.430	.494	.618	1.00	.470	.540	.579	.461
	Sig.	.044	.075	.037	.006	.	.049	.021	.012	.054
H2 W-3	Coef.	.950	.668	.771	.860	.470	1.00	.884	.680	.794
	Sig.	.000	.002	.000	.000	.049	.	.000	.002	.000
H3 W-1	Coef.	.851	.719	.725	.891	.540	.884	1.00	.631	.911
	Sig.	.000	.001	.001	.000	.021	.000	.	.005	.000
H3 W-2	Coef.	.548	.218	.507	.550	.579	.680	.631	1.00	.620
	Sig.	.019	.385	.032	.018	.012	.002	.005	.	.006
H3 W-3	Coef.	.748	.598	.825	.847	.461	.794	.911	.620	1.000
	Sig.	.000	.009	.000	.000	.054	.000	.000	.006	.

In Table 10, average scores are taken and they are shown. Considering the average scores, it is seen that the first try is the best, whereas 18th try is the worst.

Table 10. Average scores for three hybrid models

Experiment no	Average scores
1	1.000
2	0.782
3	0.610
4	0.929
5	0.728
6	0.555
7	0.842
8	0.627
9	0.536
10	0.705
11	0.579
12	0.438
13	0.623
14	0.415
15	0.331
16	0.458
17	0.323
18	0.170

3.5. Variance Analysis and Taguchi Optimization

Using average scores from Table 10, regression and variance analysis are performed in Table 11. The model is consistent at 5% significance level ($p<0.05$). The summary of the model is given in Table 12. Determination coefficient (R^2) is calculated as 99.15%. Developed model produces successful results because R^2 is nearly 1. In Table 13, coefficient table is presented. All coefficients are consistent at 5% significance level.

Table 11. ANOVA for average scores of three hybrid models

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.801	0.267	546.19	0.000
The number of revolutions	1	0.486	0.486	994.83	0.000
Tool overhang length	1	0.306	0.306	625.67	0.000
Workpiece hardness	1	0.009	0.009	18.07	0.001
Error	14	0.007	0.000		
Total	17	0.808			

Table 12. Model summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.022	99.15%	98.97%	98.45%

Table 13. Coefficients table

Term	Coefficient	SE coefficient	T value	P value
Constant	1.6430	0.0322	50.96	0.000
The number of revolutions	-0.001	2.6e-5	-31.54	0.000
Tool overhang length	-0.008	3.19e-4	-25.01	0.000
Workpiece hardness	-1.91e-4	4.5e-5	-4.25	0.000

In Figure 1, the main effects plot for means is provided. When main effects plots are examined, the lowest value of the number of revolutions, tool overhang lengths and workpiece hardness increase stable cutting depths and chatter vibrations are prevented. The results are consistent with literature [32].

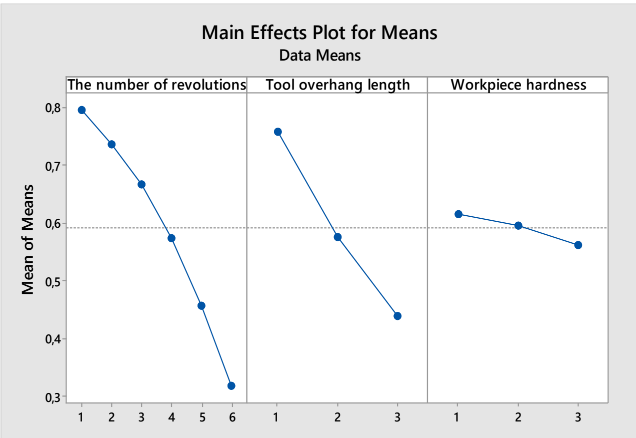

Figure 1. Main effects plot for means

3.6. Validation Study

In order to validate the model, ten validation experiments which were carried out before [31] in different cutting conditions are used. In Table 14, experimental results of stable cutting depths, hybrid MCDM scores and the rankings are given. The ranking of the model is same with experimental ranking. Experiment #8 is the best, whereas experiment #7 is the worst.

Table 14. Comparison of model and experimental results

No	Rpm	Overhang length (mm)	Hardness (HV)	S. cutting depth (mm)	MCDM score	Model ranking
1	500	70	165	6	0.634	3
2	500	80	165	5.8	0.554	5
3	500	90	165	5.5	0.474	6
4	710	90	165	4	0.302	8
5	710	70	387.5	4	0.420	7
6	710	90	387.5	3.4	0.260	9
7	710	110	387.5	3.2	0.100	10
8	180	90	124	8.2	0.744	1
9	250	90	124	7.5	0.687	2
10	355	90	124	6.8	0.601	4

4. Conclusions

In this article, a new hybrid decision making model is developed. Best-Worst method (BWM) is hybridized with TOPSIS, Grey Relational Analysis (GRA) and Weighted Sum Approach (WSA). Three different hybrid decision making models are combined. The model is tested in a turning operation to prevent chatter vibrations. The results are given below:

1. According to three experts, workpiece hardness is more effective on stable cutting depths and tool overhang length is less effective than the other factors
2. It is observed that the first try is the best, whereas 18th try is the worst for three multi criteria decision making method.
3. The rankings obtained by three models are tested with Spearman Correlation Test. At 5% significance level, the rankings are nearly same.
4. Taguchi optimization is carried out using average scores of three models because three models produce nearly same results. The lowest value of the number of revolutions, tool overhang lengths and workpiece hardness increase stable cutting depths according to main effect plots.
5. Validation study is performed to test the model. Model and experimental rankings are same. Experiment #8 is the best, whereas experiment #7 is the worst.

The developed model can be used by engineers and operators in different machining processes as milling, drilling etc. Also, an advanced decision support system might be developed in future studies.

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