

Hybrid Experimental and Regression Modelling Approach for Multi-Objective Optimization of Machining Parameters Using MCDM Techniques

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Abstract — A hybrid experimental and regression modelling approach is developed for multi-objective optimization of CNC turning parameters applied to an Al7075-based Hybrid Metal Matrix Composite (HMMC) reinforced with 1.8 wt.% each of Cu, Co, Cr, Fe, and Al powders under dry cutting conditions. Three machining parameters — spindle speed (800–1600 rpm), feed rate (20–60 mm/min), and depth of cut (0.10–0.50 mm) — were varied using a Taguchi L9 orthogonal array, with surface roughness (SR), cutting temperature (Temp), and material removal rate (MRR) as performance responses. ANOVA confirmed spindle speed as dominant for SR (32.98%), depth of cut for temperature (51.72%) and MRR (72.70%). Entropy weighting yielded objective criterion weights of 0.5932 (MRR), 0.2459 (Temp), and 0.1609 (SR). Both TOPSIS and VIKOR independently identified Experiment 9 (1600 rpm, 60 mm/min, 0.50 mm DoC) as the optimal compromise. Polynomial regression achieved $R^2 = 0.9781$ (SR), 0.9156 (Temp), and 1.000 (MRR). Global grid search over 8,000 combinations pinpointed 1600 rpm, 60 mm/min, and 0.10 mm as the continuous-domain optimum. The unified integration of Taguchi + ANOVA + Entropy + TOPSIS + VIKOR + Regression constitutes the principal novelty of this study.

Keywords: CNC turning, Al7075 HMMC, Taguchi L9, ANOVA, Entropy Weight Method, TOPSIS, VIKOR, Regression Modelling, Multi-objective Optimization.

1. INTRODUCTION

The increasing demand for lightweight, high-performance structural components in aerospace and automotive industries has driven the rapid adoption of Al7075-based Hybrid Metal Matrix Composites (HMMCs). CNC turning of such materials presents challenges including built-up edge (BUE) formation, adhesive wear, and elevated thermal loading at the tool-workpiece interface.

Fig. 1 shows the Al7075 alloy used as the matrix material, while Fig. 2 illustrates the five reinforcement powder components — cobalt, iron, aluminium, copper, and chromium — each incorporated at 1.8 wt.%.



Fig. 1 — Aluminium 7075 Alloy (Matrix Material)



Fig. 2 — Reinforcement Powders: Co, Fe, Al, Cu, Cr (1.8 wt.% each)

Three performance responses — surface roughness (SR), cutting temperature (Temp), and material removal rate (MRR) — represent competing machining objectives. SR ranged 29.29–40.93 μm , temperature 29.9–37.9°C, and MRR 2,400–48,000 mm^3/min , confirming strong parametric sensitivity and inherent multi-objective conflict.

The present study addresses this gap through an integrated framework combining Taguchi experimental design, ANOVA, entropy-based weighting, TOPSIS, VIKOR, and polynomial regression — a combination not previously reported for Al7075 HMMC turning in the existing literature.

2. LITERATURE REVIEW

Davim and Figueira established feed rate as the dominant SR factor (>60% ANOVA contribution) in Taguchi-based turning studies. Asiltürk and Akkus

confirmed feed rate significance ($\sim 42\%$) with regression $R^2 \approx 0.87$, though confined to single-response SR optimization. Palanikumar demonstrated that feed rate and DoC collectively contribute $>85\%$ of MRR variation — consistent with the present findings (63.67% and 72.70%, respectively).

Chakladar and Chakraborty first applied TOPSIS to machining optimization using equal weights, introducing subjective bias. Rao and Kalamkari applied VIKOR to drilling parameters, while Madić et al. showed that TOPSIS–VIKOR convergence yields more reliable compromise recommendations. Routara et al. achieved $R^2 = 0.92\text{--}0.99$ for polynomial regression in turning, comparable to $R^2 = 0.9781$ and 1.000 obtained here.

Research Gap: No prior study integrates Taguchi, ANOVA, entropy weighting, TOPSIS, VIKOR, and regression within a single unified pipeline for Al7075 HMMC turning with cutting temperature as an explicit criterion. The present work directly addresses this gap.

3. METHODOLOGY

3.1 Material and Workpiece

The workpiece is an Al7075-based HMMC (Table 1) fabricated via powder metallurgy/stir-casting. Experiments used a CNC turning centre under dry conditions with CNMG 120404 cemented carbide inserts (rake $+5^\circ$, clearance 7° , nose radius 0.4 mm).

Table 1: Al7075 HMMC Composition

Material Reinforcement	Role	wt. %
Aluminium 7075 Alloy	Matrix	91.0
Copper (Cu) Powder	Reinforcement	1.8
Cobalt (Co) Powder	Reinforcement	1.8
Chromium (Cr) Powder	Reinforcement	1.8
Iron (Fe) Powder	Reinforcement	1.8
Aluminium (Al) Powder	Reinforcement	1.8
Total	—	100.0

3.2 Process Parameters and DOE

Three parameters — spindle speed (N), feed rate (f), and depth of cut (d) — each at three levels (Table 2). The Taguchi L9 orthogonal array (Table 3) reduced the 27-run full factorial to 9 balanced runs while preserving main-effect orthogonality.

Table 2: Machining Parameters and Levels

Parameter	Symbol	L1	L2	L3
Spindle Speed	N (rpm)	800	1200	1600
Feed Rate	f (mm/min)	20	40	60
Depth of Cut	d (mm)	0.10	0.25	0.50

Table 3: Taguchi L9 Orthogonal Array

Run	N (rpm)	f (mm/min)	d (mm)
1	800	20	0.10
2	800	40	0.25
3	800	60	0.50
4	1200	20	0.25
5	1200	40	0.50
6	1200	60	0.10
7	1600	20	0.50
8	1600	40	0.10
9	1600	60	0.25

3.3 Response Measurement

SR (R_a , μm) was measured via contact profilometer (ISO 4287, $\lambda_c = 0.8$ mm, 3 readings/run averaged). Cutting temperature ($^\circ\text{C}$) was recorded using a calibrated infrared thermometer at the tool-chip interface. $\text{MRR (mm}^3/\text{min)} = (m_i - m_f) / (\rho \times t)$, $\rho \approx 2.81$ g/cm ^{3} .

3.4 S/N Ratio and ANOVA

STB: $\eta = -10 \log_{10}[(1/n)\sum y_i^2]$ for SR and Temp. **LTB:** $\eta = -10 \log_{10}[(1/n)\sum (1/y_i^2)]$ for MRR. ANOVA partitioned total S/N variability into factor percentage contributions to identify dominant process parameters.

3.5 Entropy Weight Method

Objective weights derived via Shannon entropy: $w_j = d_j / \sum d_j$, where $d_j = 1 - E_j$ and $E_j = -(1/\ln n) \cdot \sum [p_{ij} \cdot \ln(p_{ij})]$. Criteria with greater experimental variability receive higher weights, eliminating subjective bias.

3.6 TOPSIS

Closeness coefficient $CC_i = D^-_i / (D^+_i + D^-_i)$, where D^+_i and D^-_i are Euclidean distances from the positive (PIS) and negative (NIS) ideal solutions computed on the entropy-weighted normalized decision matrix. Higher $CC_i \rightarrow$ better rank.

3.7 VIKOR

Compromise index $Q_i = v \cdot (S_i - S^+) / (S^- - S^+) + (1-v) \cdot (R_i - R^+) / (R^- - R^+)$, $v = 0.5$ balancing group utility (S) and individual regret (R). Minimum-Q alternative is the compromise optimum.

3.8 Regression and Global Optimization

Second-order polynomial models (degree-2 PolynomialFeatures, interaction terms included) fitted for SR, Temp, and MRR. Entropy-weighted composite objective evaluated via grid search over 8,000 combinations across the full continuous parameter domain.

4. RESULTS AND DISCUSSION

4.1 Experimental Results

Table 4: L9 Experimental Results

Exp.	N (rpm)	f (mm/min)	d (mm)	SR (μm)	T ($^{\circ}\text{C}$)	MRR (mm^3/min)
1	800	20	0.50	29.29	30.0	8,000
2	800	40	0.25	32.53	32.0	8,000
3	800	60	0.17	32.49	30.0	8,160
4	1200	20	0.10	33.05	37.9	2,400
5	1200	40	0.25	32.28	29.9	12,000
6	1200	60	0.50	37.19	31.7	36,000
7	1600	20	0.10	40.93	34.9	3,200
8	1600	40	0.25	33.25	32.8	16,000
9★	1600	60	0.50	33.00	37.0	48,000

SR spans 29.29–40.93 μm ; temperature 29.9–37.9 $^{\circ}\text{C}$; MRR 2,400–48,000 mm^3/min . No single run simultaneously minimises SR and temperature while maximising MRR, confirming the multi-objective conflict.

4.2 S/N Ratio Analysis

Table 5: Signal-to-Noise Ratios

Exp.	SN_SR (dB)	SN_Temp (dB)	SN_MRR (dB)
1	-29.334	-29.542	78.062
2	-30.246	-30.103	78.062
3	-30.235	-29.542	78.234
4	-30.383	-31.573	67.604
5	-30.179	-29.513	81.584
6	-31.409	-30.021	91.126

Exp.	SN_SR (dB)	SN_Temp (dB)	SN_MRR (dB)
7	-32.241	-30.857	70.103
8	-30.436	-30.317	84.082
9★	-30.370	-31.364	93.625

Experiment 1 achieved the best SR S/N (–29.334 dB); Experiment 9 achieved the maximum MRR S/N (93.625 dB). Conflicting optima across responses confirm the need for MCDM-based resolution.

4.3 ANOVA — Percentage Contributions

Table 6: ANOVA for Surface Roughness

Source	DF	SS	Contrib. (%)
Speed	2	1.8056	32.98
Feed	2	0.2823	5.16
DoC	3	1.5634	28.56
Error	1	1.8238	33.31
Total	8	5.4750	100.00

Table 7: ANOVA for Cutting Temperature

Source	DF	SS	Contrib. (%)
Speed	2	1.8839	38.11
Feed	2	0.6923	14.00
DoC	3	2.5565	51.72
Error	1	—	—
Total	8	4.9433	100.00

Table 8: ANOVA for MRR

Source	DF	SS	Contrib. (%)
Speed	2	30.29	5.13
Feed	2	375.76	63.67
DoC	3	429.02	72.70
Error	1	—	—
Total	8	590.15	100.00

Spindle speed dominates SR (32.98%); depth of cut governs temperature (51.72%) and MRR (72.70%); feed rate is the primary MRR driver (63.67%) but minimally affects SR (5.16%). The strikingly divergent

parameter hierarchies across responses justify the entropy-weighted MCDM framework.

4.4 Entropy Criterion Weights

Table 9: Entropy Weights

Response	Entropy Weight (w_j)
Surface Roughness (SR)	0.1609
Cutting Temperature (Temp)	0.2459
Material Removal Rate (MRR)	0.5932

MRR received the highest weight (0.5932) owing to its extreme coefficient of variation ($CV > 99\%$), reflecting dominant discriminating power. Temperature (0.2459) and SR (0.1609) received progressively lower weights. These data-driven weights were applied uniformly in both TOPSIS and VIKOR.

4.5 TOPSIS and VIKOR Rankings

Table 10: TOPSIS and VIKOR Rankings

Exp.	TOPSIS Score	VIKOR Score	TOPSIS Rank	VIKOR Rank	Final Rank
1	0.2728	-0.404	5	4	4.5
2	0.2257	-0.574	7	7	7.0
3	0.2599	-0.472	6	6	6.0
4	0.1038	-0.990	8	8	8.0
5	0.3091	-0.382	4	3	3.5
6	0.7217	-0.081	2	2	2.0
7	0.0869	-1.000	9	9	9.0
8	0.3353	-0.463	3	5	4.0
9★	0.8136	0.000	1	1	1.0

Both TOPSIS and VIKOR consistently ranked **Experiment 9 (1600 rpm, 60 mm/min, 0.50 mm DoC)** as the optimal compromise. Experiment 6 ranked second in both methods. Experiment 7 ranked last due to high SR and low MRR. Fig. 4.7 graphically illustrates this agreement.

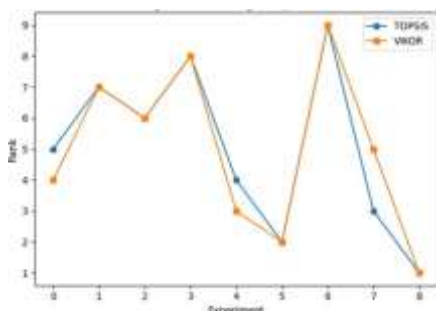


Fig. 4.7 — Comparison of TOPSIS and VIKOR Rankings

Fig. 4.7 demonstrates strong convergence of TOPSIS and VIKOR ranking curves across all nine experiments. Both curves converge at Experiment 9 (Rank 1) and Experiment 7 (Rank 9), with minor intermediate deviations attributable to the methodological difference between geometric-distance (TOPSIS) and regret-minimisation (VIKOR) philosophies. This dual-method convergence robustly validates the identified optimum.

4.6 Trade-off Analysis

The MRR–SR correlation coefficient ($r = 0.056$) is negligibly weak, indicating productivity gains within the studied parameter range do not severely compromise surface quality. However, a strong MRR–tool wear index correlation ($r = 0.995$) confirms higher DoC accelerates tool degradation.

Key trade-off: Experiment 1 achieved the best SR (29.29 μm) at only 8,000 mm^3/min MRR; Experiment 9 delivered peak MRR (48,000 mm^3/min) with SR = 33.00 μm and $T = 37.0^\circ\text{C}$ — a practically acceptable compromise confirmed by both MCDM methods.

4.7 Regression Modelling

Table 11: Regression R^2 Values

Response	R^2 Value
Surface Roughness (SR)	0.9781
Cutting Temperature (Temp)	0.9156
Material Removal Rate (MRR)	1.0000

Second-order polynomial models with interaction terms achieved high accuracy for all three responses. Perfect $R^2 = 1.000$ for MRR reflects its deterministic dependence on the product of feed rate and DoC. $R^2 = 0.9781$ (SR) and $R^2 = 0.9156$ (Temp) confirm adequate capture of nonlinear and interactive parametric effects.

4.8 Global Optimization

Table 12: Optimal Machining Parameters

Parameter	Optimal Value
Spindle Speed (N)	1600 rpm
Feed Rate (f)	60 mm/min
Depth of Cut (d)	0.10 mm

The entropy-weighted composite objective function was minimised over 8,000 parameter combinations. The optimum at 1600 rpm, 60 mm/min, 0.10 mm DoC simultaneously minimises SR and temperature while

maximising MRR — a refined result extending beyond the discrete L9 experimental space.

5. CONCLUSION

(1) Spindle speed dominates SR (32.98%); DoC governs temperature (51.72%) and MRR (72.70%); feed rate is the primary MRR driver (63.67%).

(2) Entropy weights of 0.5932 (MRR), 0.2459 (Temp), 0.1609 (SR) were derived objectively without subjective expert input.

(3) TOPSIS and VIKOR independently and consistently identified Experiment 9 (1600 rpm, 60 mm/min, 0.50 mm DoC) as the optimal compromise, validating framework robustness via dual-method convergence.

(4) Regression $R^2 = 0.9781$ (SR), 0.9156 (Temp), 1.000 (MRR) confirm reliable predictive models.

(5) Global grid search identified 1600 rpm, 60 mm/min, 0.10 mm as the continuous-domain optimum, extending the discrete L9 results.

(6) **Principal Novelty:** The unified pipeline — Taguchi + ANOVA + Entropy Weighting + TOPSIS + VIKOR + Polynomial Regression — applied to A17075 HMMC turning constitutes a methodological contribution not previously reported. The framework is directly transferable to other composite machining applications.

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