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Lathe CNC Machine Tool Evaluation by Exploring Grey Set based Full Multiplicative Form Approach

Ms. Varsha Kailas Ladke*[1] & Dr. Hulas Raj A. Tonday[2]

Department of Mechanical Engineering, Shreeyash College of Engineering, Cha. Sambhajinagar, Maharashtra State, India[1,2]

Abstract: Computer Numerical Control (CNC) machine tools play a vital role in modern advanced manufacturing environments, where precision, efficiency, and reliability are critical. Evaluating CNC machines involves multiple conflicting criteria, making the decision-making process complex, particularly under conditions of uncertainty and incomplete information. Conventional evaluation techniques often lack the capability to effectively address such ambiguity. To overcome these limitations, this study proposes a comprehensive evaluation and benchmarking model for lathe CNC machine tools based on grey system theory. The proposed framework is structured using a SLS and focuses exclusively on key performance criteria and relevant metrics to ensure practical applicability. Grey set theory is incorporated into the model to manage uncertainty, vagueness, and incomplete data inherent in real-world decision environments. Furthermore, a grey-based crisp Full Multiplicative Form (FMF) approach is applied to rank and benchmark the alternative CNC lathe machines. The results demonstrate the effectiveness and robustness of the proposed approach in identifying the most suitable CNC machine tool among multiple alternatives. The study concludes by highlighting the practical implications and reliability of the model for decision-makers in advanced manufacturing systems.

Keywords: CNC Machine Tools, Grey Set Theory, Benchmarking, MCDM, Manufacturing Systems, Full Multiplicative Form Approach, MCDM

I. INTRODUCTION

Advanced Manufacturing Systems (AMS) represent a significant transformation in contemporary industrial practices, fundamentally reshaping how products are designed, manufactured, and delivered. These systems integrate advanced technologies such as Computer Numerical Control (CNC), automation, robotics, artificial intelligence (AI), the Internet of Things (IoT), and data analytics to enhance productivity, precision, flexibility, and overall operational efficiency. As a result, AMS has become a critical enabler of competitiveness and innovation in modern manufacturing environments.
Within AMS, CNC machine tools play a pivotal role due to their capability to deliver high precision, repeatability, and efficiency in complex machining operations. However, evaluating CNC machine tools is a challenging task because it involves multiple, often conflicting criteria such as accuracy, cost, productivity, reliability, and maintenance requirements. Traditional evaluation approaches are frequently inadequate in handling uncertainty, vagueness, and incomplete information inherent in real-world decision environments. To address these limitations, Grey set theory has been increasingly adopted as a robust and effective tool for decision-making under uncertainty.

Decision-making is a fundamental component of the evaluation process. It involves analyzing various criteria to select the most suitable alternative in uncertain and complex situations. Decision analysis considers both objective data and subjective judgments provided by individual decision-makers or groups. The quality of information used in decision-making can range from precise, scientifically derived data to qualitative assessments and expert opinions. This variability necessitates the use of systematic methods capable of processing diverse types of information efficiently and effectively, ultimately leading to more reliable decisions.

In this context, Multi-Criteria Decision-Making (MCDM) methods have gained widespread acceptance due to their ability to handle complex decision problems involving multiple conflicting criteria. MCDM aims to identify the most appropriate alternative by evaluating and ranking options based on a set of defined criteria. The process of comparing and ranking alternatives under similar criteria is commonly referred to as benchmarking. This study adopts an MCDM-based benchmarking approach to evaluate CNC machine tools, as illustrated in Fig. 1.

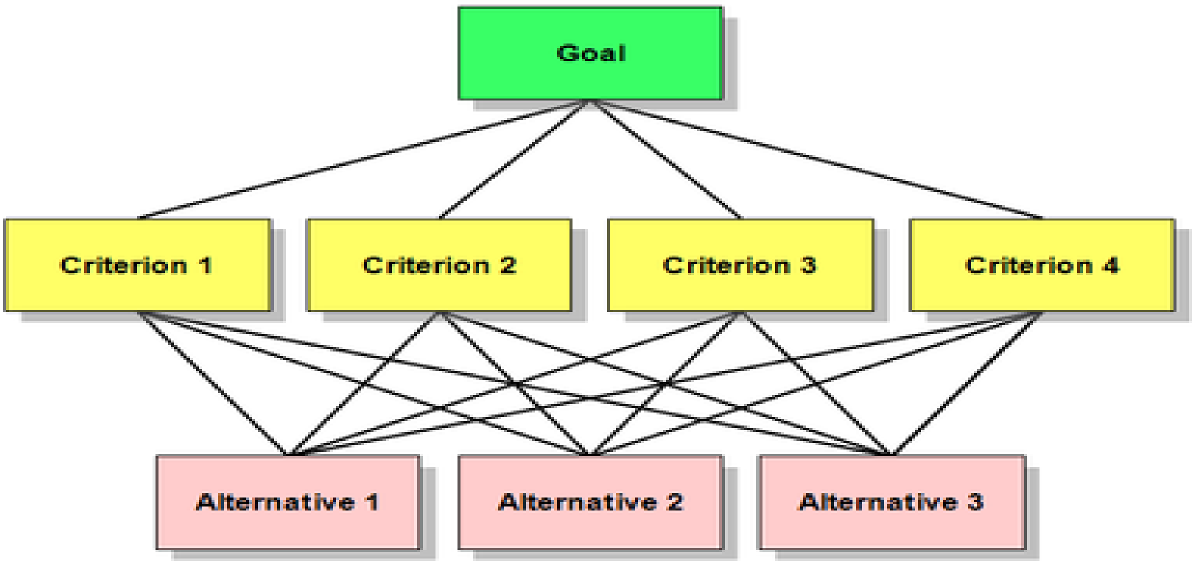

Fig. 1: MCDM benchmarking model

2. LITERATURE REVIEW

Author(s) & Year	*Objective*	*Technique*	*Key Criteria*	*Key Findings*
Wang et al. (2020)	To evaluate CNC machine tool performance under uncertainty	Grey Relational Analysis (GRA)	Surface roughness, machining accuracy, tool capacity, cost	GRA effectively ranks CNC alternatives under incomplete information
Kumar & Singh (2020)	Benchmark CNC machines for manufacturing industries	Fuzzy TOPSIS	Productivity, precision, Maintenance cost, reliability	Fuzzy approach handles vagueness in expert judgment effectively
Li et al. (2021)	Multi-criteria evaluation of CNC turning machines	Grey-Fuzzy hybrid model	Speed, feed rate, Power consumption, accuracy	Hybrid model improves decision accuracy compared to standalone methods
Zhang & Chen (2021)	Selection of CNC machining centers	Interval Grey Numbers	Operational cost, flexibility, quality	Grey numbers capture uncertainty in industrial environments
Patel et al. (2021)	Performance benchmarking of CNC milling machines	Fuzzy AHP-GRA	Machine capability, tool life, Power consumption	Combined model enhances ranking consistency
Singh et al. (2022)	Evaluate CNC machine alternatives using uncertainty modeling	Type-1 Fuzzy Logic	Reliability, processing time, cost	Fuzzy models reduce ambiguity in decision-making
Liu et al. (2022)	Benchmarking CNC machining systems	Grey-DEMATEL	Interrelationships among performance factors	DEMATEL identifies causal relationships effectively
Sharma & Gupta (2022)	CNC machine selection using hybrid MCDM	Fuzzy VIKOR + GRA	Cost, flexibility, precision, productivity	Hybrid model improves compromise solution identification

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Balezentis & Zeng (2022)	Interval-valued fuzzy decision making	Interval fuzzy sets	Performance efficiency, Virtual reality for Operator, Responses on Repeated Operations	Improves reliability of evaluation
Huang et al. (2022)	Evaluate health status of CNC machines	Grey Clustering + Fuzzy Comprehensive Evaluation	Operator health & Safety indicators, operational	Hybrid approach effectively determines machine health grades under uncertainty
Zhang et al. (2022)	Improve prediction accuracy in CNC machining	Grey Wolf Optimization + Grey Prediction Model	Schedule Utilization, prediction accuracy	Optimization improves forecasting capability of CNC systems
Mamledesai et al. (2022)	Optimize machining parameters	Fuzzy Logic Controller (FLC)	Cutting speed, feed rate, depth of cut	Fuzzy controller improves machining efficiency and adaptability
Gucuyener (2022)	Monitor tool wear in CNC milling	Fuzzy Decision System	Vibration, motor power, tool capacity	Achieved -90% accuracy in tool wear detection
Yigit (2023)	Multi-criteria evaluation using fuzzy logic	Fuzzy MCDM	Cost, quality, flexibility, Working Automation, Flexibility for Production	Effective ranking under uncertainty
Sahu et al. (2023)	Grey set theory-based benchmarking	Grey Set + MCDM	Delivery time, quality Index, operational efficiency	Grey set handles incomplete and imprecise data effectively
Verma & Rao (2023)	Sustainable CNC machine evaluation	Fuzzy Multi-objective optimization	Energy consumption, emissions, Six Sigma index, Functionality Control, Closed Loop Controlling	Sustainability improves decision-making frameworks
Huang et al. (2024)	CNC machine tool selection under uncertainty	Intuitionistic Fuzzy TOPSIS	Risk, reliability, performance	Improved handling of hesitation uncertainty
Das & Mishra (2024)	CNC machining benchmarking framework	Grey-Fuzzy Integrated Model	Productivity, cost, environmental impact	Hybrid model provides robust evaluation
Ali et al. (2024)	Smart CNC system evaluation	Fuzzy IoT-based decision model	Machine health, Zero Defects, Product Quality Index, Stress less Operation	IoT integration enhances monitoring and evaluation
Yadav & Kumar (2025)	Advanced benchmarking of CNC machines	Grey-Fuzzy DEMATEL-TOPSIS	Interdependency, performance metrics, Green Management Operator Comfort	Hybrid model improves ranking accuracy and causal analysis
Subramanian et al. (2025)	Advanced fuzzy decision frameworks	q-rung orthopair fuzzy sets	Ambiguity, decision confidence	Enhanced flexibility in decision-making
Liu et al. (2025)	Develop CNC equipment health evaluation system	Grey Fuzzy Clustering + Whitening Weight Function	System components, fault indicators, OC)-34 Ease to Maintenance, Clean, downtime, efficiency	Provides structured evaluation framework for CNC subsystems
Gupta et al. (2025)	Detect anomalies in CNC machines	Fuzzy Logic-based Expert System	Machine health, anomalies, operational deviations	Real-time anomaly detection improves system reliability

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3. LITERATURE SUMMARY

Recent studies on CNC machine tool evaluation and benchmarking highlight a strong shift toward advanced Multi-Criteria Decision-Making (MCDM) techniques integrated with fuzzy logic and grey system theory to address uncertainty and complexity. Early works, such as Wang et al. (2020) and Kumar & Singh (2020), focused on performance evaluation and benchmarking using Grey Relational Analysis (GRA) and Fuzzy TOPSIS, considering key factors like surface quality, productivity, and cost. Subsequent research introduced hybrid models, including grey-fuzzy approaches and fuzzy AHP-GRA (Li et al., 2021; Patel et al., 2021), to enhance decision accuracy by combining multiple methodologies.

From 2022 onwards, there is a clear trend toward incorporating uncertainty modeling, interrelationship analysis, and system-level evaluation using methods such as Grey-DEMATEL, Fuzzy VIKOR, and Type-1 fuzzy logic (Liu et al., 2022; Sharma & Gupta, 2022). Studies also began integrating emerging technologies, including IoT, optimization algorithms, and predictive models, to improve machine performance, health monitoring, and operational efficiency.
Overall, the literature demonstrates a progressive evolution from basic evaluation models to integrated, intelligent, and sustainability-oriented decision frameworks for CNC machine tool benchmarking under uncertainty.

4. RESEARCH OBJECTIVES

- Develop a Grey Set-based evaluation model.
- Identify critical CNC performance criteria and metrics.
- To build the criteria and metrics model (up to 2nd level) especially for lathe CNC machine tool to effectively describe CNC performance mapping.
- Lack of robust grey approach, can benchmark lathe CNC machine tool under above proposed model (mixed information).

5. MODEL DEVELOPMENT

Table.1-represents the model, is shown in below is used for assessing performance of lathe CNC machine tool.

Table.1: A CNC machine tool evaluation and benchmarking theoretical model

Model	**Nature of model criteria**	**Ist Level**	**Metrics (2nd Level)**
Lathe CNC Evaluation Benchmarking	**Subjective (S)**	Production Controlling (PC)-C_1	Virtual reality for Operator (VRO)- C11
			Responses on Repeated Operations (RROs)- C12
			Schedule Utilization (SU)- C13
			Working Automation (WA)- C14
			Flexibility for Production (FP)- C15
		Defects Outcomes (ZDOs)-C_2	Six Sigma index (SSI)- C21
			Ease Functionality Control (EFC)-C22
			Closed Loop Controlling (CLC)- C23
			Zero Defects vs. Changing Operations (ZDsCOs)-C24
			Product Quality Index (PQI)- C25
		Comfort and Healthy (C&H)-C_3	Stress less Operation for Operator (SlOsO)- C31
			Green Management (GM)- C32
			Safety& Health (S&H)-33
			Operator Comfort (OC)-34
			Ease to Maintenance and Daily Clean (EMDC)-35
		Cost (C), INR-C4	
		Tool Capacity (TC),No.-C_5	

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	Objective (O)	Requirement of Space (RS),Inch,-C_6	
		Maintenance Cost (MC),INR/Year-C_7	
		Depreciations (D),Year-C_8	
		Power Consumption (PC),Unit/Hrs-C_9	

6. METHODOLOGY

- **Normalization of evaluated crisp ratings**:

$$r_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^{2}}} \tag{1}$$

- **Full Multiplicative Form (FMF) Approach:**
  This approach believes on multification of criteria. In formulae, R^{ij} denotes i^{th} CNC lathe machine tool alternative of j^{th} criteria. Usually these numbers belong to the interval [0, 1]. These criteria are added (if desirable value subjected to maximization or subtracted (if desirable value subjected to minimization), thus the summarizing index of each alternative is derived in this

$$A_i = \frac{\prod_{j=1}^{n-\max} R_{ij}}{\prod_{j=1}^{n-\min} R_{ij}} \tag{2}$$

7. EMPIRICAL RESEARCH: LATHE CNC MACHINE TOOL EVALUATION

It is assume a steel pipe production company is existing in India, want to make thread on pipes. That company needs the lathe CNC machine tool for that. The company decided to purchase the best one lathe CNC machine tool from Sellers Company. The model is presented in Table.1. The grey set rating scale is shown in Table.2. The objective criteria data proposed by Sellers Company is given in Table. 3.

The evaluation procedure is here:

- ***Normalization of crisp value from Grey set rating***:
  The assigned grey set ratings by ten experts, is aggregated and crisp value is evaluated by Harefa et al., 2024, is shown in Table.4-11. Next, Metrics rating (in the terms for aggregated grey set) are converted to first level criteria by using Simamora et al., 2024, Sharma & Gupta (2022).
- ***Evaluation of normalized ratings of criteria and FMF approach:***
  A normalized decision making technique is proposed here. After obtaining the crisp value from aggregated grey set, the normalization of criteria is carried out by Equa.1 and Equa.2 is applied as FMF technique to evaluate the results are shown in Table.12-13.

8. CONCLUSION

The findings reveal that CNC Lathe–VII secured the highest overall ranking among all evaluated alternatives, underscoring its strong ability to satisfy multi-dimensional performance requirements, as illustrated in Fig. 2. Its leading position is primarily due to its well-balanced performance across both subjective measures and objective criteria. In contrast to other alternatives that excelled only in specific aspects, CNC Lathe–VII demonstrated consistently high performance across all evaluation parameters. This consistency highlights its operational excellence as well as its capacity to deliver long-term cost efficiency, a crucial factor in industrial decision-making processes. FMF is applied to calculate the results, shown in Table. 12-13.

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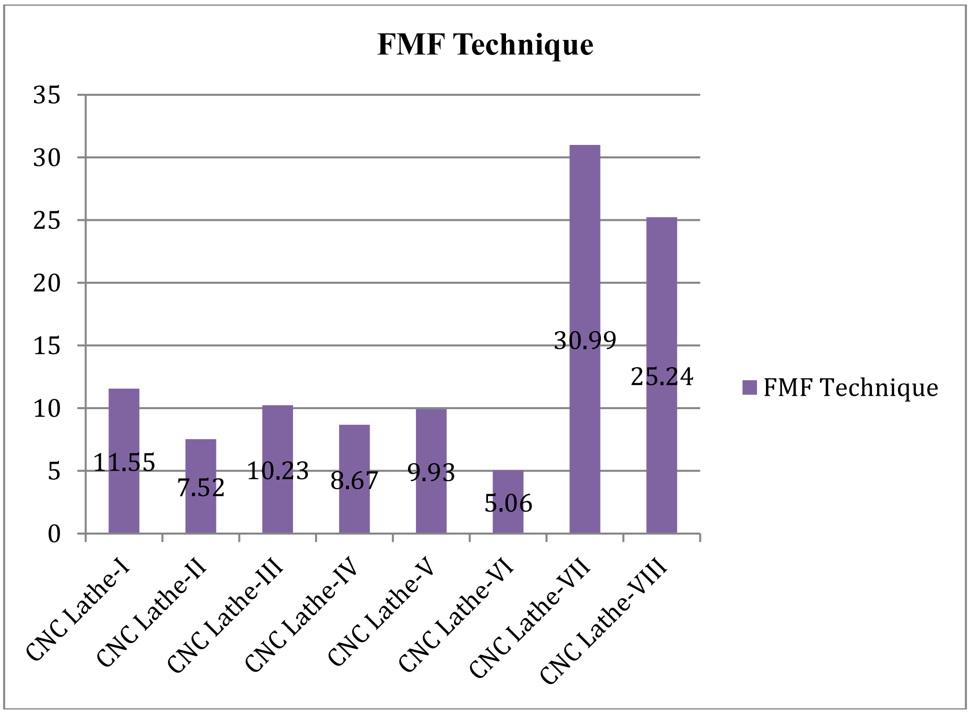

Fig.2**:** Preference orders of alternative CNC Lathe machine tools under mixed data by FMF technique

REFERENCES

[1]. Simamora, W. S., Harahap, S. S., Idaman, A., & Simatupang, S. (2024). Analysis of the MOORA method in determining pilot areas at PT XYZ. Journal of Computer Networks, Architecture and High Performance Computing, 6(3), 1098–1106.

[2]. Harefa, S., Sihombing, V., & Juledi, A. P. (2024). Decision support system for gas station location selection using MOOSRA. Jurnal Teknik Informasi dan Komputer (Tekinkom), 7(2), 917–923.

[3]. Wang, Y., Liu, H., & Chen, X. (2020). Performance evaluation of CNC machine tools under uncertainty using grey relational analysis. Journal of Manufacturing Systems, 54, 112–121.

[4]. Kumar, R., & Singh, P. (2020). Benchmarking CNC machines using fuzzy TOPSIS approach. International Journal of Advanced Manufacturing Technology, 108(3–4), 985–997.

[5]. Li, Z., Zhang, Y., & Wu, Q. (2021). Multi-criteria evaluation of CNC turning machines using a grey-fuzzy hybrid model. Journal of Intelligent Manufacturing, 32(5), 1345–1358.

[6]. Zhang, H., & Chen, L. (2021). Selection of CNC machining centers based on interval grey numbers. Grey Systems: Theory and Application, 11(2), 210–223.

[7]. Patel, D., Shah, R., & Mehta, K. (2021). Performance benchmarking of CNC milling machines using fuzzy AHP–GRA approach. International Journal of Production Research, 59(18), 5560–5575.

[8]. Joshi, V., & Kumar, H. (2021). Optimization of CNC lathe turning: A review of technique, parameter and outcome. In Lecture Notes in Mechanical Engineering. Springer.

[9]. Singh, A., Verma, S., & Rao, K. (2022). Evaluation of CNC machine alternatives using type-1 fuzzy logic. Applied Soft Computing, 114, 108089.

[10]. Liu, J., Wang, Z., & Huang, Y. (2022). Benchmarking CNC machining systems using grey-DEMATEL approach. Expert Systems with Applications, 190, 116189.

[11]. Sharma, M., & Gupta, V. (2022). CNC machine selection using hybrid fuzzy VIKOR and GRA method. Computers & Industrial Engineering, 165, 107948.

[12]. Balezentis, T., & Zeng, S. (2022). Interval-valued fuzzy decision-making approaches for performance evaluation. Technological and Economic Development of Economy, 28(2), 345–362.

[13]. Huang, X., Li, P., & Zhao, J. (2022). Health evaluation of CNC machines using grey clustering and fuzzy comprehensive evaluation. Measurement, 188, 110536.

[14]. Zhang, Y., Sun, Q., & Li, H. (2022). Improving prediction accuracy in CNC machining using grey wolf optimization and grey prediction model. Journal of Manufacturing Processes, 68, 245–256.

[15]. Mamledesai, S., Kulkarni, P., & Patil, R. (2022). Optimization of machining parameters using fuzzy logic controller in CNC machining. Materials Today: Proceedings, 62, 4215–4220.

DOI: 10.17148/IJIREEICE.2026.14710

[16]. Gucuyener, E. (2022). Tool wear monitoring in CNC milling using a fuzzy decision system. Measurement Science Review, 22(3), 145–152.
[17]. Yigit, T. (2023). Multi-criteria evaluation using fuzzy MCDM methods under uncertainty. Scientific Reports, 13, 4567.
[18]. Sahu, A. K., Mishra, R., & Das, S. (2023). Grey set theory-based benchmarking using MCDM techniques. Grey Systems: Theory and Application, 13(1), 89–104.
[19]. Verma, P., & Rao, N. (2023). Sustainable CNC machine evaluation using fuzzy multi-objective optimization. Sustainable Production and Consumption, 35, 512–523.
[20]. Huang, X., Li, Y., & Chen, Z. (2024). CNC machine tool selection under uncertainty using intuitionistic fuzzy TOPSIS. Journal of Manufacturing Systems, 72, 115–128.
[21]. Das, R., & Mishra, P. (2024). CNC machining benchmarking framework using a grey-fuzzy integrated model. International Journal of Production Research, 62(8), 2456–2472.
[22]. Ali, M., Khan, S., & Ahmed, R. (2024). Smart CNC system evaluation using a fuzzy IoT-based decision model. Journal of Intelligent Manufacturing, 35(5), 1890–1905.
[23]. Yadav, V., & Kumar, A. (2025). Advanced benchmarking of CNC machines using grey-fuzzy DEMATEL-TOPSIS approach. Computers & Industrial Engineering, 185, 109567.
[24]. Subramanian, N., Ravi, V., & Suresh, R. (2025). Advanced fuzzy decision frameworks based on q-rung orthopair fuzzy sets. Applied Soft Computing, 154, 110234.
[25]. Liu, H., Zhang, W., & Zhao, L. (2025). Development of CNC equipment health evaluation system using grey fuzzy clustering and whitening weight function. Reliability Engineering & System Safety, 245, 109876.
[26]. Gupta, S., Sharma, K., & Verma, D. (2025). Anomaly detection in CNC machines using a fuzzy logic-based expert system. Journal of Manufacturing Processes, 78, 321–335.

TABLES APPENDIX

Table.2: The grey set based linguistic scale for ratings and weights

Linguistic Scale (Ratings)	Grey set Scale
Very Poor (VP)	[0, 1]
Poor (P)	[1, 3]
Medium Poor (MP)	[3, 4]
Fair (F)	[4, 5]
Medium Good (MG)	[5, 6]
Good (G)	[6, 9]
Very Good (VG)	[9, 10]

Table: 3: CNC lathe machine tools alternative (A_i) with objective database

Evaluation of CNC lathe machine tools alternative (A_i)	(C_4)	(C_5)	(C_6)	(C_7)	(C_8)	(C_9)
CNC Lathe-I	16000000	6	49	51000	16	2
CNC Lathe-II	15000000	5	50	52000	14	3
CNC Lathe-III	17000000	6	50	50000	17	2
CNC Lathe-IV	18000000	8	47	53000	18	3
CNC Lathe-V	19000000	7	50	50000	19	2
CNC Lathe-VI	19000000	7	50	50000	19	4
CNC Lathe-VII	12000000	8	52	54000	10	2
CNC Lathe-VIII	10000000	8	50	50000	11	3

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Table.4: Linguistics ratings assessed by K^{th} experts vs. C_{JK} (subjective metrics) in the terms of grey set and evaluated aggregated grey set for CNC-Lathe-I

C_{jk}	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}
C11	P	MG	VP	VP	P	MP	P	P	MG	VP
C12	MP	P	P	P	MP	F	MP	MP	P	P
C13	F	P	MP	MP	F	MG	F	F	P	MP
C14	MG	MP	F	F	MG	G	MG	MG	MP	F
C15	G	F	MG	MG	G	VG	G	G	F	MG
C21	VG	MG	G	G	VG	G	VG	VG	MG	G
C22	G	MP	VG	VG	G	VG	G	G	MP	VG
C23	VG	F	G	MP	VG	MP	VG	VG	F	G
C24	MP	MG	VG	F	MP	F	MP	MP	MG	VG
C25	F	G	MP	G	F	G	F	F	G	MP
C31	G	VG	F	MP	G	G	G	G	VG	F
C32	VG	VG	G	F	VG	MP	VG	VG	VG	G
C33	MP	MP	VG	G	MP	F	MP	MP	MP	VG
C34	F	MG	MG	MG	F	G	F	F	MG	MG
C35	F	VG	G	VG	F	VG	F	F	VG	G

Table 5: Linguistics ratings assessed by K^{th} experts vs. C_{JK} (subjective metrics) in the terms of grey set and evaluated aggregated grey set for CNC-Lathe-II

C_{jk}	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}
C11	G	MG	G	G	G	G	MG	VG	G	G
C12	VG	MP	VG	VG	VG	VG	MP	G	VG	VG
C13	MP	F	MP	MP	G	MP	F	VG	MP	G
C14	F	MG	F	F	VG	F	MG	MP	F	VG
C15	G	G	G	G	MP	G	G	F	G	MP
C21	MP	VG	G	MP	F	G	VG	G	G	F
C22	F	VG	MP	F	G	MP	VG	VG	MP	G
C23	G	MP	F	G	VG	F	MP	MP	F	VG
C24	MG	MG	G	MG	MG	G	MG	F	G	MG
C25	VG	VG	VG	VG	G	VG	VG	F	VG	G
C31	F	MP	G	F	F	G	MP	MG	G	F
C32	MG	F	VG	MG	MG	VG	F	G	VG	MG
C33	VP	MG	MP	VP	VP	MP	MG	P	MP	VP
C34	P	P	F	P	P	F	P	MP	F	P
C35	MP	P	MG	MP	MP	MG	P	F	MG	MP

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Table.6: Linguistics ratings assessed by K^{th} experts vs. C_{JK} (subjective metrics) in the terms of grey set and evaluated aggregated grey set for CNC-Lathe-III

C_{jk}	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}
C11	MP	VG	G	MP	F	G	VG	G	G	F
C12	F	VG	MP	F	G	MP	VG	VG	MP	G
C13	G	MP	F	G	VG	F	MP	MP	F	VG
C14	MG	MG	G	MG	MG	G	MG	F	G	MG
C15	VG	VG	VG	VG	G	VG	VG	F	VG	G
C21	F	MP	G	F	F	G	MP	MG	G	F
C22	MG	F	VG	MG	MG	VG	F	G	VG	MG
C23	VP	MG	MP	VP	VP	MP	MG	P	MP	VP
C24	P	P	F	P	P	F	P	MP	F	P
C25	MP	P	MG	MP	MP	MG	P	F	MG	MP
C31	G	MG	G	G	G	G	MG	VG	G	G
C32	VG	MP	VG	VG	VG	VG	MP	G	VG	VG
C33	MP	F	MP	MP	G	MP	F	VG	MP	G
C34	F	MG	F	F	VG	F	MG	MP	F	VG
C35	G	G	G	G	MP	G	G	F	G	MP

Table.7: Linguistics ratings assessed by K^{th} experts vs. C_{JK} (subjective metrics) in the terms of grey set and evaluated aggregated grey set for CNC-Lathe-IV

C_{jk}	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}
C11	P	P	F	P	P	F	P	MP	F	P
C12	MP	P	MG	MP	MP	MG	P	F	MG	MP
C13	G	MG	G	G	G	G	MG	VG	G	G
C14	VG	MP	VG	VG	VG	VG	MP	G	VG	VG
C15	MP	F	MP	MP	G	MP	F	VG	MP	G
C21	F	MG	F	F	VG	F	MG	MP	F	VG
C22	G	G	G	G	MP	G	G	F	G	MP
C23	G	MP	F	G	VG	F	MP	MP	F	VG
C24	MG	MG	G	MG	MG	G	MG	F	G	MG
C25	VG	VG	VG	VG	G	VG	VG	F	VG	G
C31	F	MP	G	F	F	G	MP	MG	G	F
C32	MG	F	VG	MG	MG	VG	F	G	VG	MG
C33	VP	MG	MP	VP	VP	MP	MG	P	MP	VP
C34	MP	VG	G	MP	F	G	VG	G	G	F
C35	F	VG	MP	F	G	MP	VG	VG	MP	G

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Table.8: Linguistics ratings assessed by K^{th} experts vs. C_{JK} (subjective metrics) in the terms of grey set and evaluated aggregated grey set for CNC-Lathe-V

C_{jk}	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}
C11	VP	MG	VP	VP	VG	MP	VP	VG	VG	VP
C12	G	MG	G	G	MP	F	G	MP	MP	G
C13	MG	P	MP	MG	F	G	MG	F	F	MP
C14	MP	MP	F	MP	F	F	MP	F	F	F
C15	MG	F	MG	MG	F	VG	MG	F	F	MG
C21	MG	MG	G	MG	MG	G	MG	MG	MG	G
C22	MG	MP	VG	MG	MG	VG	MG	MG	MG	VG
C23	F	MG	G	F	G	MP	F	G	G	G
C24	F	MP	VG	F	G	F	F	G	G	VG
C25	G	VG	G	G	G	G	G	G	G	G
C31	MP	F	F	MP	G	F	MP	G	G	F
C32	F	F	G	F	VG	F	F	VG	VG	G
C33	G	MP	G	G	MP	F	G	MP	MP	G
C34	MG	MG	MG	MG	F	G	MG	F	F	MG
C35	VG	VG	G	VG	F	VG	VG	F	F	G

Table 9: Linguistics ratings assessed by K^{th} experts vs. C_{JK} (subjective metrics) in the terms of grey set and evaluated aggregated grey set for CNC-Lathe-VI

C_{jk}	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}
C11	MG	F	MG	MG	F	VG	MG	F	F	MG
C12	MG	MG	G	MG	MG	G	MG	MG	MG	G
C13	MG	MP	VG	MG	MG	VG	MG	MG	MG	VG
C14	F	MG	G	F	G	MP	F	G	G	G
C15	F	MP	VG	F	G	F	F	G	G	VG
C21	G	VG	G	G	G	G	G	G	G	G
C22	MP	F	F	MP	G	F	MP	G	G	F
C23	F	F	G	F	VG	F	F	VG	VG	G
C24	VP	MG	VP	VP	VG	MP	VP	VG	VG	VP
C25	G	MG	G	G	MP	F	G	MP	MP	G
C31	MG	P	MP	MG	F	G	MG	F	F	MP
C32	MP	MP	F	MP	F	F	MP	F	F	F
C33	G	MP	G	G	MP	F	G	MP	MP	G
C34	MG	MG	MG	MG	F	G	MG	F	F	MG
C35	VG	VG	G	VG	F	VG	VG	F	F	G

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Table.10: Linguistics ratings assessed by K^{th} experts vs. C_{JK} (subjective metrics) in the terms of grey set and evaluated aggregated grey set for CNC-Lathe-VII

C_{jk}	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}
C11	F	MG	G	F	G	MP	F	G	G	G
C12	F	MP	VG	F	G	F	F	G	G	VG
C13	G	VG	G	G	G	G	G	G	G	G
C14	MP	F	F	MP	G	F	MP	G	G	F
C15	F	F	G	F	VG	F	F	VG	VG	G
C21	MP	MP	F	MP	F	F	MP	F	F	F
C22	G	MP	G	G	MP	F	G	MP	MP	G
C23	MG	MG	MG	MG	F	G	MG	F	F	MG
C24	VG	VG	G	VG	F	VG	VG	F	F	G
C25	MG	F	MG	MG	F	VG	MG	F	F	MG
C31	MG	MG	G	MG	MG	G	MG	MG	MG	G
C32	MG	MP	VG	MG	MG	VG	MG	MG	MG	VG
C33	VP	MG	VP	VP	VG	MP	VP	VG	VG	VP
C34	G	MG	G	G	MP	F	G	MP	MP	G
C35	MG	P	MP	MG	F	G	MG	F	F	MP

Table.11: Linguistics ratings assessed by K^{th} experts vs. C_{JK} (subjective metrics) in the terms of grey set and evaluated aggregated grey set for CNC-Lathe-VIII

C_{jk}	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}
C11	MP	F	F	MP	G	F	MP	G	G	F
C12	F	F	G	F	VG	F	F	VG	VG	G
C13	MP	MP	F	MP	F	F	MP	F	F	F
C14	G	MP	G	G	MP	F	G	MP	MP	G
C15	MG	MG	MG	MG	F	G	MG	F	F	MG
C21	VG	VG	G	VG	F	VG	VG	F	F	G
C22	MG	F	MG	MG	F	VG	MG	F	F	MG
C23	G	MG	G	G	MP	F	G	MP	MP	G
C24	MG	P	MP	MG	F	G	MG	F	F	MP
C25	MG	MG	G	MG	MG	G	MG	MG	MG	G
C31	MG	MP	VG	MG	MG	VG	MG	MG	MG	VG
C32	VP	MG	VP	VP	VG	MP	VP	VG	VG	VP
C33	F	MG	G	F	G	MP	F	G	G	G
C34	F	MP	VG	F	G	F	F	G	G	VG
C35	G	VG	G	G	G	G	G	G	G	G

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Table.12: Lathe CNC machine tool evaluation score by MOORA technique

A_i^{th}	FMF Technique
CNC Lathe-I	11.55798
CNC Lathe-II	7.523555
CNC Lathe-III	10.23412
CNC Lathe-IV	8.673549
CNC Lathe-V	9.939014
CNC Lathe-VI	5.061222
CNC Lathe-VII	30.99509
CNC Lathe-VIII	25.24733

Table.13: Lathe CNC machine tool preference orders by FMF technique

A_i^{th}	FMF Technique
Computed presence orders	
CNC Lathe-I	3
CNC Lathe-II	7
CNC Lathe-III	4
CNC Lathe-IV	6
CNC Lathe-V	5
CNC Lathe-VI	8
CNC Lathe-VII	1
CNC Lathe-VIII	2

