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A novel HGEDM method for evaluating 3-axis CNC machines in green environment under uncertainty

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A B S T R A C T

In the face of digitization in manufacturing industries, the judicious evaluation and selection of cutting-edge CNC machines play a pivotal role in achieving production-grade precision, accuracy and manufacturing agility. The evaluation of 3-axes CNC machines incorporates most sought-after subjective and objective criteria having significant relative weights and green impacts. This research paper presents a novel heterogeneous expert based decision making (HGEDM) framework incorporating a diversified combination of experts having distinct impact factors. The experts' impact factors so calculated impart significant contributions in computing weighted aggregated performance ratings of the alternatives. To establish the effectiveness of the suggested approach, three practical selection problems are illustrated. The calculated findings are validated with few well-established approaches demonstrating the realistic nature of the suggested methodology. To assess the stability and robustness of the proposed approach, a sensitivity analysis is performed. Besides, Spearman's rank correlation measure demonstrates that the ranks obtained using the proposed approach are highly close to those derived from several existing methods. Furthermore, both Pearson correlation coefficient and Sample correlation coefficient measures show a strong association between the proposed approach and existing ones. Therefore, the proposed HGEDM approach is considered to be a consistent and effective tool for supporting optimal selection.

1. Introduction

The globalized business scenario demands for green and sustainable manufacturing solutions which motivates manufacturers to invest in advanced CNC (Computer Numerical Control) machine tools and other computer-controlled equipment. These technologies not only improve sustainability but also enhance overall manufacturing capabilities, including efficiency, quality, production-grade accuracy and precision. CNC machining provides benefits like reduced surplus material and decreased machining time throughout different stages of manufacturing. By optimizing cutting paths and minimizing unnecessary movements, CNC machines can significantly reduce the amount of material waste during the production process and contribute to a more sustainable approach to manufacturing. The incorporation of CNC machine tools into IoT (Internet of Things) enables seamless integration between CNC machining systems, central computing systems, and other mechanical equipment. This integration allows for continuous monitoring, data analysis and enhancement of manufacturing practices resulting in increased efficiency and reduced resource consumption. CNC machining, being electronic, inherently reduces the carbon footprint compared to conventional machining methods that may rely more heavily on physical processes. The major characteristic advantage of CNC machines involves the electronic transfer of CAD files between end customers and manufacturers that minimize the need for physical transportation of design specifications. This reduces carbon emissions associated with transportation and logistics, contributing to a more sustainable manufacturing ecosystem. In this research article the assessment of CNC machine performance involves the consideration of a significant number of conflicting criteria including the incorporation of green criteria.

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1.1 Green attributes in performance assessment

This research paper suggests a comprehensive diverse expert based decision making aid for the assessment of 3 axes-CNC machines under a green environment. The effective selection of CNC machines not only addresses the customer oriented demands but also aligns with the green manufacturing process. Figuring out the lack of adequate information on green criteria in existing literature, this paper emphasizes on environmental impact to promote cleaner production processes. The green criteria considered include Energy utilization, toxic effect, dust pollution effect and local eco- friendly materials usage.

Energy utilization: The optimal use of automated manufacturing facilities can lead to significant power saving to a considerable extent. Minimal energy consumption can be achieved by energy-efficient equipment and Process optimization. CNC machine tools are equipped with energy controlling systems that monitor energy consumption in real time and adjust machining operations accordingly. Artificial intelligence (AI) enabled CNC machines have the unique feature of analyzing manufacturing processes to identify inefficiencies and implementing changes to minimize energy waste leading to lowering carbon footprint. CNC-based digital manufacturing systems can indeed contribute to addressing this crucial green criterion and implementing sustainable practices in advanced manufacturing processes.

Toxic effect: The exposure of CNC personnel to toxic chemicals used in abrasive slurry in wire-cut EDM systems, suspended dust particles from CNC router applications and coolants in CNC horizontal lathe machines are significant concerns for workplace safety and health. These chemicals can indeed pose severe health hazards if proper safety measures are not taken. The CNC manufacturing facilities are equipped with toxic fumes and dust arresting systems to reduce the risk of such hazardous exposure to CNC machinists and technicians.

Dust pollution effect: Dust generated during CNC machining operations can contain fine particulate matter, metal particles, and other airborne contaminants that can degrade air quality in the surrounding atmosphere. Inhalation of dust particles generated during CNC router application and EDM process can lead to respiratory problems, cardiovascular issues and other health complications to the CNC operators. Equipping CNC machines with dust collectors is essential for maintaining a clean and safe working environment by ensuring minimal dispersion of harmful dust particles into the surrounding atmosphere. This arrangement offers several benefits such as machine longevity, quality product and regulatory compliance.

Local eco-friendly material usage in CNC machine components: The local material usage in CNC machine tool components can have significant positive impact on the environment particularly in terms of reducing transportation related emissions. By sourcing materials locally the manufacturers can minimize transportation distance that reduces fuel consumption by trucks, ships, or other modes of transport. It results in lowering associated CO_2 emissions. Local sourcing also tends to be more energy-efficient as shorter transportation distances require less energy overall. Another significant advantage of availability of local materials is to support an economic boost to the local suppliers, distributors and manufacturers. This leads to a positive impact on the community. Furthermore, the availability of local materials in the vicinity helps the manufacturers and suppliers increase substantial resilience to geopolitical turbulence and natural adversities and thus ensures continuity of manufacture with minimal negative impact on the environment.

Integrating green attributes with manufacturing systems and transforming into a green economy are critical steps towards achieving sustainable development. Prioritizing sustainability is indispensable for businesses and economies aiming to ensure a prosperous and resilient future. Based on the comprehensive result and analysis from green performance assessment, the proposed HGEDM approach not only enhances the evaluation quality and strengthens the decision-making process but also supports productivity, reliability and sustainability in advanced digital manufacturing processes. However, the evaluation and selection process is a complex and challenging managerial task for decision makers due to the intricate technological implications and the involvement of diverse experts.

1.2 Heterogeneity and homogeneity in group decision-making approach

This research article develops a systematic approach for assessing and selecting CNC machines by considering heterogeneity among decision-makers to improve decision quality. Here some salient features are presented to highlight the insights about heterogeneous and homogeneous expert groups. The perspective on heterogeneous expert group is as follows:

Diverse perception: Heterogeneous groups consist of individuals with varied backgrounds, expertise, and viewpoints. This diversity can lead to a richer pool of ideas and insights, as members bring different knowledge and experiences to the table.

Innovative solutions: The combination of diverse viewpoints often sparks originality and improvement in problem-solving. Heterogeneous groups are more likely to generate novel results in multifaceted problems due to the wide range of perspectives represented.

Enhanced problem Understanding: Different members of a heterogeneous group may interpret problems differently based on their backgrounds and expertise. This can lead to a more comprehensive understanding of the problem, allowing for a more detailed and informed selection process.

Abridged groupthink: The heterogeneous groups are less vulnerable to groupthink which refers to the practice of group decision-making (GDM) that often leads to lower-quality decision outcomes. The presence of diverse viewpoints boosts constructive discussion and challenges related to critical selection.

Comprehensive stakeholder representation: Prioritizing sustainability leads to broader stakeholder representation by developing comprehensive decision-making, improving responsibility, and building stronger relationships with employees, manufacturers, suppliers, distributors, investors, and customer communities.

The perspective on homogeneous expert group is as follows:

Shared understanding: This shared understanding can enable effective communication building and teamwork as experts are likely to have similar backgrounds, expertise, and perceptions.

Efficacy: Homogeneous expert groups may share common principles, goals, and values that lead to quicker decision-making processes with less conflict as compared to heterogeneous groups.

Focus on proficiency: The homogeneous expert group can examine carefully into technical details and intricacies with occasional interdisciplinary association. This homogeneity adopts an environment where experts can quickly reach a generally accepted opinion on complicated issues and emphasize on cutting-edge topics. Their similar proficiency ensures that everybody can formulate possible solutions to decision making problems.

Group reliability: Homogeneous group experts often exhibit resilient social interconnection and amity among group members resulting in fostering confidence and cooperation. This can improve team dynamism and efficiency in decision-making as group members feel free to express their views and opinion within a supportive environment.

Aligned decision: The experts belonging to homogeneous groups may share more or less similar priorities and ideas that lead to alignment in decision-making aftermaths. This could be predominantly beneficial in situations where consensus is imperative for implementation and accomplishment in the selection process.
A heterogeneous group, by considering a wide range of interests and concerns, tends to produce more inclusive and reasonable decision outcomes than a homogeneous group of experts. The direction of the present diverse expert-based green evaluation is inevitably influenced by the contributions of several prominent researchers, who have enhanced the decision-making strategy.

1.3 Literature review

In relation to the fourth industrial revolution, where advanced technologies like CNC machines play a crucial role in the most modern computerized manufacturing systems. The contributions of previous researchers have indeed paved the way for modern research trends. Their work has influenced decision-making models and approaches in selecting the most appropriate CNC machine to enhance product quality and optimize the manufacturing process. The substantial contributions of past research have laid a strong foundation for the current trends in decision-making research related to evaluation of CNC machines. Here, the research inputs of a few leading researchers in the field of CNC machine evaluation are presented. Dutta, Bairagi and Dey (2024) proposed a selection framework for assessing and selecting 3-axes CNC turning centers based on both technical and green criteria using input from a diverse group of experts. The framework aims to assess the significance of various conflicting attributes in order to analyze the performance of these CNC machine tools. By considering both technical and green aspects, this decision approach tried to promote sustainability in manufacturing processes while also ensuring optimal performance. Yusuf and Mustafa (2022) developed a novel approach to selecting machining centers that prioritizes long-term performance optimization. This methodology evaluates and scores critical structural components of machining centers to rank alternatives. Specifically, attributes such as precision, stiffness, damping capability and Temperature resilience were considered using fuzzy triangular numbers to account for uncertainty and imprecision. They aimed to provide a more comprehensive and nuanced understanding of machining center capabilities. Sahin and Aydemir (2022) developed a decision making model to evaluate the most preferred and least preferred alternatives from feasible alternatives of CNC based machine tools. In the context of evaluating and choosing CNC machine tools, they found the technique most suitable for decision-making and prioritization. Yang et al. (2021) developed a MCDM approach in combination with TOPSIS to identify weakness and limitation associated with feasible alternatives, evaluating and selecting subcomponents in high-performance CNC lathe machines tools. Li et al. (2020) provided a comprehensive approach by integrating FDEMATEL, the entropy method, and the VIKOR method for evaluating machine tools. This approach allows decision-makers to consider the interrelationships between criteria, assign appropriate weights to them, and rank alternatives effectively, ultimately facilitating informed decision making in choosing the best machine tool for a given application. Patil and Kothavale (2020) devised an AHP based MCDM approach specifically aimed at ranking the sub components of CNC turning centers. Vafadar, Rad and Hayward (2019) introduced an integrated decision framework aimed at assisting decision-makers in making informed and judicious decisions regarding flexible drilling machines.

DU et al. (2019) aimed to suggest a comprehensive selection framework consisting of Entropy method, AHP and Extension theory to evaluate and select the most suitable remanufactured high-performance machining system. This approach allows for a systematic and rigorous evaluation process, leading to informed decisions that account for multiple aspects of the problem. Breaz, Bologa, Racz and Crenganis (2019) suggested a FAHP decision framework for selecting the most suitable CNC-based turning center. Ding, Jiang, Zhang, Cai and Liy (2018) integrated AHP with the modified TOPSIS method to evaluate CNC machine components specifically focusing on guide ways for machining systems. Camci et al. (2018) developed a decision model using hesitant fuzzy analytic hierarchy to assist in selecting CNC routers for woodwork industries. Mondal et al. (2017) suggested a MADM decision model for evaluating CNC machine tool alternatives. They utilized Data Envelopment Analysis (DEA) as a tool to aid in proper decision-making for selecting the best alternative. Kabak and Dağdeviren (2017) developed a hybrid approach that aims to provide an effective solution to the CNC machines evaluation problem. They integrated the benefits of both ANP and GRA to support the decision-making framework. Chakraborty and Boral (2017) developed an amalgamated decision-making approach consisting of human cognitive processes and artificial intelligence for CNC machine tool selection. Such a system would aim to streamline the often complex and multi-faceted process of selecting the right CNC machine tools for specific manufacturing tasks. Vafadar, Hayward and Tolouei-Rad (2017) developed a structured approach to evaluating and selecting special purpose drill machine tools (SPDMT). They proposed a simulated model utilizing genetic algorithms to determine the optimal process parameters and drill machine tool configuration. During the selecting of drill machine tools, they set the primary objective as maximum profit based on SPDMT configuration, number of machining units and required tool feed and cutting speed for each machining operation. Wu et al. (2016) developed a MCGDM decision model for evaluating feasible CNC machine tools. They employed the fuzzy-VIKOR method for this purpose. In their decision model, the decision-makers' preferences were expressed using subjective variables to weigh the significance of criteria and evaluate performance. Bologa et al. (2016) introduced a decision-making model aimed at evaluating 3-axis and 5-axis CNC machines. Their approach leveraged MATLAB software and fuzzy system to facilitate the best decision-making process. Bologa et al. (2016) devised an AHP based decision model tailored specifically for evaluating 5-axis CNC machines. Nguyen et al. (2015) proposed a combined method to assist in making informed decisions regarding the evaluation of the competitive CNC machines. Their approach involved integrating Fuzzy AHP and Fuzzy COPRAS within a MADM model. Prasad and Chakraborty (2015) adopted a quality function deployment approach in conjunction with visual BASIC 6.0 for effective evaluation and selection of the most suitable CNC turning centers for an advanced manufacturing industry. Sahu, Datta and Mahapatra (2015) formulated a decision framework combining fuzzy and VIKOR compromise ranking method to evaluate and select the best feasible CNC machine tool. Nguyen et al. (2014) established a comprehensive decision model to aid in the assessment of the most competitive CNC machine tools. Their approach involved integrating fuzzy ANP and COPRAS-G within a MADM framework utilizing the group of decision makers. Aghdaie et al. (2013) developed a MADM model for evaluating CNC machine tools. Their approach incorporated COPRAS-G and SWARA. Tho et al. (2013) suggested an integrated decision model consisting of fuzzy-Entropy and TOPSIS approach for evaluating and selecting CNC machine tools. The Entropy was employed to compute criteria weights. TOPSIS was adopted to prioritize the feasible alternatives. Ayag and Ozedemir (2012) introduced a hybrid MCDM method for performance assessment of CNC machine tools. Their methodology integrated two techniques: modified TOPSIS and Fuzzy ANP). Ic et al. (2012) devised an AHP based decision model specifically tailored for the performance assessment of CNC machining center components. Ilangkumaran et al. (2012) proposed a decision framework involving FAHP and VIKOR for evaluating and selecting the most suitable CNC machine tool out of feasible alternatives.

Taha and Rostam (2011) devised a comprehensive decision-making approach consisting of FAHP and PROMETHEE for choosing CNC turning centers. They incorporated MATLAB for evaluating different criteria weights to select the best option. Taha and Rostam (2011) suggested a decision-making approach which integrates fuzzy AHP and ANN to select the horizontal computer controlled turning center for a computerized manufacturing system. Ozgen et al. (2011) suggested a comprehensive decision framework to evaluate the feasible CNC press machine tools. By combining PROMETHEE, modified DELPHI and FAHP, they aim to capture various aspects of decision-making and handle uncertainties inherent in the selection process. Samdevi et al. (2011) employed a combined MCDM approach aiming to leverage the strengths of both fuzzy logic and grey relational analysis to improve the stability and reliability of their selection process. They integrated fuzzy AHP and GRA methods to evaluate vertical CNC machining systems. Wang et al. (2010) proposed a fuzzy MADM technique aimed at assisting decision-making processes concerning the selection of appropriate CNC machine tools for a mechanized manufacturing enterprise. Athawale and Chakrabarty (2010) suggested a decision framework aimed at evaluating the feasible CNC machine tools alternatives. Their approach involved applying the TOPSIS method to evaluate feasible CNC lathe machine tools. Alberti, Ciurana, Rodriguez and Ozel (2009) contributed to the development of a decision-making tool for assessing high-speed milling machine tools. Their approach involved considering both the machine specifications and process parameters. Ic and Yurdkul (2009) contributed to the field of decision-making in CNC machining centers by developing a MCDM technique. Their approach involved incorporating fuzzy logic into the TOPSIS. Yurdalul and İç (2009) applied Fuzzy TOPSIS as the MCDM approach for ranking CNC machine tools based on multiple criteria. The paper aims to assess and quantify how employing fuzzy numbers in MCDM models enhances decision-making compared to using crisp (non-fuzzy) numbers. Balaji et al. (2009) adopted the ELECTRE decision model for evaluating and selecting a machine tool for a flexible manufacturing system. Dagdeviren (2008) suggested an integrated MCDM model to assist in selecting the most suitable CNC milling machine tool. Their approach involved integrating two well-known decision-making techniques: the AHP and the PROMETHEE. Onut et al. (2008) contributed to the field of assessing CNC milling machines by integrating the Fuzzy TOPSIS. In their work, they utilized a fuzzy AHP to evaluate conflicting criteria weights. Durán and Aguilo (2008) proposed a fuzzy AHP based decision model aimed to evaluate and select CNC machine tools for an advanced manufacturing industry. Sun et al. (2008) proposed a comprehensive decision model to optimize CNC machine tool selection in manufacturing context. They combined AHP and Grey relational analysis approaches for dealing with complex decision-making criteria and preferences. Ayag (2007) developed an integrated decision making technique consisting of simulation techniques and fuzzy AHP for assessing feasible alternatives, particularly in the context of choosing the optimal CNC horizontal turning center. Cimren et al. (2006) made a valuable contribution to the field of evaluating CNC machine tools by developing a MCDM technique. Their approach involved employing the AHP to select the best alternative specifically considering subjective decision criteria related to machine specifications to develop a comprehensive decision making approach. Ayag and Ozdemir (2005) contributed to the field of assessing and selecting CNC vertical turning centers by adopting a fuzzy AHP approach. Their work aimed to evaluate a set of feasible alternatives and identify the most suitable CNC vertical turning center. Based on a comprehensive review of the existing literature, several unaddressed findings related to this research are summarized in Table 1.

Table 1
Comprehensive literature review and identification of research gaps

N.	Authors and year	Approaches	Area of application	Identification of research gaps
1	Dutta et al. (2024)	Group decision based MCDM approach	3 axes CNC machining and CNC turning centers	Inadequacy in expert' s impact factor consideration, Insufficiency in green criteria
2	Yusuf et al. (2022)	fuzzy based strategic evaluation methodology	Machining center	GDM approach, green criteria and expert' s impact factor consideration
3	Sahin et al. (2021)	Best-Worst technique	CNC Machines	Inadequacy in expert' s impact factor consideration uncertainty, objective criteria
4	Yang et al. (2021)	WRM	machine tools subsystem	GDM approach, green criteria and expert' s impact factor consideration
5	Li et al. (2020)	DEMATEL, entropy & VIKOR	CNC machine tool	Expert' s impact factor consideration, green criteria
6	Patil et al. (2020)	AHP	sub-systems of the CNC turning center	Inadequacy in green criteria and GDM approach
7	Vafadar et al. (2019)	Hybrid feasibility analysis	flexible drill machine	GDM approach and green criteria
8	DU et al. (2019)	AHP-entropy weight & extension theory	Remanufactured basic heavy-duty machine tool	GDM approach, green criteria and expert' s impact factor consideration
9	Breaz et al. (2019)	AHP and fuzzy logic	CNC turning center	GDM approach, green criteria and expert' s impact factor consideration
10	Ding et al. (2018)	AHP & CD-TOPSIS	Guide ways for CNC machine tool	Expert' s impact factor consideration, green criteria
11	Camci et al. (2018)	Hesitant FAHP method	CNC wood router	GDM approach, green criteria and expert' s impact factor consideration
12	Mondal et al. (2017)	Data Envelopment Analysis	Computer controlled machine tool	GDM approach, green criteria, and uncertainty
13	Kabak et al. (2017)	ANP & Grey relational analysis	CNC Machine tool	GDM approach, green criteria and expert' s impact factor consideration
14	Chakraborty et al. (2017)	Case-based reasoning approach	CNC Machine tool	GDM approach, green criteria and uncertainty
15	Vafadar et al. (2017)	Genetic algorithms-based decision model	Special purpose drill machine tool	GDM approach, green criteria and expert' s impact factor consideration
16	Wu et al. (2016)	MCGDM & FVIKOR	CNC machining systems	Expert' s impact factor consideration, green criteria
17	Bologa et al. (2016)	Fuzzy set & MATLAB	Multi axes CNC vertical milling machines	GDM approach, green criteria
18	Bologa et al. (2016)	AHP	5-axes machine tools	GDM approach, green criteria
19	Nguyen et al. (2015)	Fuzzy AHP & Fuzzy COPRAS	CNC machine tool	Expert' s impact factor consideration, green criteria
20	Prasad et al. (2015)	QFD with visual BASIC 6.0	CNC turning center	GDM approach, green criteria and expert' s impact factor consideration
21	Sahu et al. (2015)	VIKOR compromise ranking method	CNC machine tool	GDM approach, green criteria and expert' s impact factor consideration
22	Nguyen et al. (2014)	Fuzzy ANP & COPRAS-G	CNC machine tool	Quantitative attributes, green criteria
23	Aghdaie et al. (2013)	SWARA & COPRAS-G	CNC machine tool	GDM approach, uncertainty, green criteria
24	Tho et al. (2013)	Intuitionistic fuzzy Entropy and TOPSIS	CNC machine tool	GDM approach, green criteria and expert' s impact factor consideration
25	Ayag et al. (2012)	Improved TOPSIS & fuzzy ANP with alpha-cut	CNC machine tool	GDM approach, green criteria, expert' s impact factor consideration
26	Ic et al. (2012)	AHP	CNC machining center components	GDM approach, green criteria, expert' s impact factor consideration
27	Ilangkumaran et al. (2012)	VIKOR and Fuzzy AHP	CNC machine tool	GDM approach, green criteria

Table 1
Comprehensive literature review and identification of research gaps (Continued)

N.	Authors and year	Approaches	Area of application	Identification of research gaps
28	Taha et al. (2011)	Integrated FAHP-PROMETHEE	CNC turning center	GDM approach, green criteria
29	Taha et al. (2011)	FAHP–ANN	CNC turning center	GDM approach, green criteria
30	Ozgen et al. (2011)	Modified DELPHI, FAHP and PROMETHEE	CNC based Press machine tool	GDM approach, green criteria
31	Samvedi et al. (2011)	FAHP & Grey relational analysis	Vertical CNC machining centers	GDM approach, green criteria
32	Wang et al. (2010)	FMADM	CNC milling & CNC lathe machine tools	GDM approach, green criteria
33	Athawale et al. (2010)	TOPSIS	CNC lathe machine tools	GDM approach, green criteria, uncertainty
34	Alberti et al. (2009)	ANN	CNC milling machine	GDM approach, green criteria
35	Ic et al. (2009)	MACSEL	CNC vertical machining centers	GDM approach, green criteria
36	Yurdalul et al. (2009)	Fuzzy TOPSIS	CNC machine tools	GDM approach, green criteria
37	Balaji et al. (2009)	ELECTRE	Machine tool	GDM approach, green criteria
38	Dağdeviren. M (2008)	AHP and PROMETHEE	Basic milling machine	GDM approach, green criteria
39	Onut et al. (2008)	FTOPIS & FAHP	CNC machining center	GDM approach, green criteria
40	Duran et al. (2008)	FAHP	CNC machine tool	GDM approach, green criteria
41	Sun et al. (2008)	FAHP and GRA	CNC machine tool	GDM approach, green criteria
42	Ayag (2007)	AHP and Simulation	CNC lathe machine	GDM approach, green criteria
43	Cimren et al. (2006)	AHP	CNC machine tool	GDM approach, green criteria
44	Ayag et al. (2005)	FAHP	CNC Vertical turning center	GDM approach, green criteria

From past researches it is clear that earlier researchers comprehensively utilized fuzzy AHP, ANP and other MCDM approaches integrated with well-established methods to formulate decision-making problems. These approaches provide robust results in evaluating and ranking viable alternatives integrating both quantitative and qualitative criteria (Li et al., 2020). The FANP encompasses the capabilities of AHP by combining fuzzy logic which improves its ability to manage uncertainty and vagueness in expert decisions. However fuzzy ANP has its own limitations in handling vague information. Besides, fuzzy ANP faces challenges in computing complex decision-making problems. However, literature survey also clears that few earlier researchers formulated a group of expert-based decision-making approaches integrating green attributes for assessing and selecting the most suitable alternative. Another unaddressed issue from detailed literature review found is insufficiency in green impact within MCDM. Addressing inadequacies in green factors within the Decision-Making approach involves environmental factors associated with CNC machining systems when evaluating and selecting the most suitable alternatives. The lack of considering green factors in evaluation processes may influence the efficacy of the decision-making approach related to eco-friendly performance. Moreover, Insufficiencies found in earlier research include considering experts' impact factors and group decision approach. These significantly affect the accuracy, reliability and effectiveness of decision-making processes. Improper consideration of experts' impact factors might lead to biased decisions. If certain experts' weight is not properly assigned, this can affect the objectivity of the decision outcomes.

To address these challenges associated with performance evaluation and selection of CNC machines, three real-world numerical examples on three different types of CNC machines unaddressed in the previous findings, have been chosen to exemplify the proposed decision-making approach. Based on a detailed literature review, three CNC machines have been selected for the assessment and selection process: Heavy-duty Gantry-type 3-axis CNC Wood Routers, 3-axes CNC Wire-cut EDM machines, and Horizontal 3-axis CNC Lathe machines. The originalities of the suggested HGEDM approach include the following:

i) A novel decision-making methodology based on the impact factors of heterogeneous experts is developed for evaluating the performance of selected alternatives under conditions of uncertainty.
ii) The impact factor assigned to each heterogeneous expert is based on their mutually appraised judgment capability, ensuring that the relative expert weights are more realistic and precisely reflect their proficiency.
iii) A few key environmental considerations are incorporated in green evaluation and selection of CNC machines.
This research paper is systematized as outlined: Segment 1 presents a comprehensive literature survey and identification of unaddressed issues. Segment 2 presents a suggested HGEDM approach for decision-centric assessment of chosen alternatives. Segment 3 presents three practical numerical examples and explanations derived from the management decision problem. Segment 4 presents the findings and analysis of the practical examples. Segment 5 presents comprehensive conclusions and directions for further research exploration.

2. Proposed HGEDM approach

This segment outlines the suggested method for assessing the performance of feasible alternatives. The suggested approach is formulated as follows:

Step 1: A decision matrix is formed by each expert containing performance ratings of the alternatives against each criterion. It helps in making decisions by scoring each option against a set of criteria. In the following matrix A_1, A_2, A_m are *m* alternatives and $C_1, C_2 \ldots C_n$ are *n* criteria with respect to which alternatives are to be evaluated. $C_1, C_2, \ldots C_k$ are objective criteria assessed in crisp number and $C_{k+1}, C_{k+2} \ldots C_n$ are subjective criteria evaluated by linguistic variables. x_{ij} represents the performance rating of i^{th} alternative against j^{th} criterion. It is noted that number of decision matrix is equal to number of experts.

A_i/C_j	C_1	C_2	…	C_k	C_{k+1}	C_{k+2}	…	C_n
A_1	x_{11}	x_{12}	…	x_{1k}	$x_{1(k+1)}$	$x_{1(k+2)}$	…	x_{1n}
A_2	x_{21}	x_{22}	…	x_{2n}	$x_{2(k+1)}$	$x_{2(k+2)}$	…	x_{2n}
…	…	..	…	…	…	…	…	…
A_m	x_{m1}	x_{m2}	…	x_{mk}	$x_{m(k+1)}$	$x_{m(k+2)}$	…	x_{mn}

Step 2: In Step 2, each expert (*k*) constructs a pairwise comparison matrix to evaluate the comparative significance of criteria ($C_1, C_2 \ldots C_n$). The matrix is structured in such a way that each criterion is compared against every other criterion. The diagonal elements of the matrix are always put 1, signifying that each criterion has equal importance when compared to itself. The off-diagonal elements represent the relative importance of one criterion over another with the value in the (i, j) position indicating how much more important criterion (C_i) is compared to criterion (C_j). This process results in a matrix where (GM_j) represents the geometric mean of the comparisons for criterion (*j*). The pairwise comparison matrix helps in quantifying subjective judgments and is essential for deriving weights for each criterion, facilitating a more structured decision-making process.

Expert *k*	C_1	C_2	----	C_n	GM_j	pv_j
C_1	1	a_{12}	----	a_{1n}	$(1 \times a_{12} \times a_{1n})^{\frac{1}{n}}$	pv_1
C_2	a_{21}	1	-----	a_{2n}	$(a_{21} \times 1 \times a_{2p})^{\frac{1}{n}}$	pv_2
----	-----	-----	-----	-----	--------	
C_n	a_{n1}	a_{n2}	-----	1	$(a_{n1} \times a_{n2} \ldots \times 1)^{\frac{1}{n}}$	pv_n

$$pv_j = \frac{GM_{jk}}{\sum_{j=1}^{n} GM_{jk}} \tag{1}$$

where $j = 1, 2 \ldots\ldots\ldots n,\quad k = 1,2,3 \ldots\ldots\ldots n$

The Eq.(1) represents a priority vector or proportional value (p_{vj}) for a given index (*j*), where (*j*) ranges from 1 to *n* and *k* ranges from 1 to p. Here, GM_{jk} denotes a specific value associated with both indices (*j*) and (*k*). The numerator (GM_{jk}) is divided by the sum of all (GM_{jk}) values. This formula essentially normalizes (GM_{jk}) by the total sum of (GM_{jk}) values, ensuring that p_{vj} represents the proportion of GM_{jk} relative to the total sum. This type of equation is often used in statistical analysis and data normalization to compare individual components within a dataset.

Step 3: In Step 3, the criteria weight computation involves calculating the weight of each criterion, denoted as w_j. This is done using the Eq. (2), where p represents the total number of experts, and pv_{jk} is the value assigned by the kth expert for the j_{th} option. Essentially, this step averages the values of each expert across all options to determine their relative importance. This weighted average helps in arranging the criteria in order of their computed weights, ensuring a more balanced and objective decision-making process.

$$w_j = \frac{1}{p} \sum_{k=1}^{p} pv_{jk} \tag{2}$$

Step 4: It involves creating an expert weight matrix that systematically organizes the evaluations given by a set of experts across various factors. In this matrix, each row represents an expert (denoted as Expert 1 through Expert *p*), and each column corresponds to a different factor (from factor 1 to factor q). The values in the matrix (such as e_{11}, e_{12}, e_{p1}, e_{p2}, etc.) indicate the weight or assessment assigned to each expert against each factor. For instance, Expert 1 may be assigned weights of e_{11} and e_{12} against factor 1 and factor 2, respectively, while expert p is assigned weights e_{p1}, e_{p2}, and so on with respect to the corresponding factors. This structured approach allows for a quantitative aggregation of expert weights, facilitating further analysis and decision-making based on the consensus or divergence of views among the experts.

	factor 1	factor 2	--------	factor q
Expert 1	e_{11}	e_{12}	------	e_{1q}
Expert 2	e_{21}	e_{22}	------	e_{2q}
-------	------	-------	-------	-------
Expert p	e_{p1}	e_{p2}		e_{pq}

Step 5: The conversion of linguistic variables of the expert weight matrix into fuzzy numbers involves transforming qualitative assessments provided by experts into quantitative fuzzy values. Each expert provides linguistic evaluations (e.g., “high,” “medium,” “low”) for various factors, which are then mapped to corresponding fuzzy numbers using predefined membership functions. This process ensures that the subjective judgments of experts are systematically quantified, allowing for the aggregation and analysis of the data. The resulting fuzzy numbers signify the degree of membership of each factor in the fuzzy set, facilitating more adaptable and flexible decision-making processes.

Step 6: In Step 6 of aggregating expert weights, the goal is to combine the individual weights assigned by multiple experts into a single set of aggregated weights. This is done by calculating the average of the lower, middle and upper bounds provided by each expert. Here p is the total number of experts. This process ensures that the aggregated weights reflect a consensus view, balancing the different perspectives and uncertainties expressed by the experts. By averaging these values, the method accounts for the variability and confidence levels of the experts’ judgments, leading to a more robust and reliable aggregated weight.

	factor 1	factor 2	--------	factor q
Expert 1	f_{11}	f_{12}	------	f_{1q}
Expert 2	f_{21}	f_{22}	------	f_{2q}
-------	------	-------	-------	-------
Expert p	f_{p1}	f_{p2}		f_{pq}

$$(\bar{l},\bar{m},\bar{u})=\left(\frac{\sum l_{ks}}{p},\frac{\sum m_{ks}}{p},\frac{\sum u_{ks}}{p}\right) \tag{3}$$

Step 7: This Step involves the defuzzification of the aggregated expert weight matrix utilizing a specific formula for computing crisp output values from fuzzy inputs. Where g_{ki} represents the defuzzified crisp output related to expert k for the i^{th} criterion. In this formula, 'α' denotes the number of points in the triangular fuzzy number, which helps normalize the sum of the lower, middle, and upper bounds of the fuzzy weights (l_{ks}, m_{ks}, and u_{ks}). By averaging these sums over the number of points (p), this defuzzification process transforms the imprecise fuzzy data into a precise representation, allowing for easier interpretation and application in decision-making contexts. It is important to verify all calculations and relationships when implementing this process.

$$g_{ki}=\frac{1}{\alpha}\left(\frac{\sum l_{ks}}{p}+\frac{\sum m_{ks}}{p}+\frac{\sum u_{ks}}{p}\right) \tag{4}$$

Step 8: In Step 8, normalizing the expert weight matrix involves adjusting the weights provided by each expert so that they are on a comparable scale. This is achieved using the Eq. (5). Here k represents the row index (ranging from 1 to the number of experts) and l represents the column index (ranging from 1 to the number of factors). Here g_{kl} is the original weight assigned by the k^{th} expert to the l^{th} factor. The normalization process divides each weight g_{kl} by the sum of all weights in the corresponding row, ensuring that the normalized weights h_{kl} sum to 1 for each expert. This step is crucial for standardizing the weight matrix, allowing for fair comparison and aggregation of expert opinions across different factors.

$$h_{kl}=\frac{g_{kl}}{\sum_{k=1}^{p} g_{kl}} \tag{5}$$

where $k = 1, 2 \ldots\ldots p$ and $l = 1, 2 \ldots\ldots q$

Step 9: In Step 9, the effective aggregate value of expert weight is calculated using the Eq. (6). This involves summing up the values of h_{kl}, which represent the individual weights or contributions of various experts. The sum of these weights is then used as the exponent in the exponential function. The exponential function denoted as (*exp*) is the mathematical constant e ≈ 2.71828 to the power of the sum of h_{kl}. This calculation transforms the summed weights into a single aggregate value, effectively capturing the combined influence of all experts in a non-linear manner, which can be particularly useful in scenarios where the impact of expert opinions grows exponentially rather than linearly.

$$a = \exp\left(\sum_{l=1}^{q} h_{kl}\right) \tag{6}$$

Step 10: In Step 10, the impact factor (IF) of each expert is calculated using the Eq. (7). This process involves summing the weights (h_{kl}) for each expert (Ek) and then taking the exponential of this sum. The numerator of the formula is the exponential of the sum of weights for a specific expert, while the denominator is the sum of the exponentials of the sums of weights for all experts. This normalization ensures that the sum of all impact factors equals 1, effectively distributing the total influence among all experts proportionally. This method captures the relative importance of each expert's contribution in a non-linear manner, emphasizing those with higher summed weights more significantly.

$$(IF)_k = \frac{\exp\left(\sum_{l=1}^{q} h_{kl}\right)}{\sum_{k=1}^{p}\left(\exp\left(\sum_{l=1}^{q} h_{kl}\right)\right)} \tag{7}$$

where $k = 1,2 \ldots\ldots p$ and $l = 1,2 \ldots\ldots q$

Such that $\sum_{k=1}^{p} (IF)_k = 1$

Step 11: In Step 11, the defuzzification of the performance rating of the decision matrix, initially expressed in Step 1, is carried out using specific formulas for objective and subjective criteria. For objective criteria, the defuzzified performance rating (r_{ij}^{k}) is directly equal to the original value (x_{ij}). For subjective criteria, the defuzzified performance rating (r_{ij}^{k}) is calculated as the average of three values: the lower limit, the middle value, and the upper limit, using the Eq. (8). Here, *k* ranges from 1 to *p* and *j* ranges from 1 to q, ensuring that all criteria are appropriately defuzzified. This process converts the fuzzy performance ratings into crisp values, facilitating clearer decision-making by providing a single, definitive performance rating for each criterion.

$$r_{ij}^{k} = \left\{ \begin{array}{l} x_{ij}, \text{ for } j \in \text{objective criteria} \\ \frac{1}{3}\left(\mu_{i(k+j)}^{l} + \mu_{i(k+j)}^{m} + \mu_{i(k+j)}^{u}\right) \end{array} \right\} \tag{8}$$

where $i = 1,2 \ldots\ldots m$ and $j = 1,2 \ldots\ldots n$

Step 12: For benefit criteria normalization, for each performance rating, calculate the ratio of the individual rating to the maximum rating. Apply the exponential function to this ratio. Sum up these normalized values across all performance criteria. For cost criteria normalization**,** determine the minimum rating for each performance criterion. Compute the inverse ratio by dividing the minimum rating by the individual rating. Again, sum up these normalized values across all criteria. By following these steps, we establish a consistent scale for evaluating performance, enabling fair comparisons. The provided equations facilitate this process.

$$t_{ij}^{k}=\frac{\exp\left(\frac{r_{ij}^{k}}{\underset{i}{\mathrm{Max}}\ r_{ij}^{k}}\right)}{\sum_{i=1}^{m}\exp\left(\frac{r_{ij}^{k}}{\underset{i}{\mathrm{Max}}\ r_{ij}^{k}}\right)},\text{for benefit criteria} \tag{9}$$

$$t_{ij}^{k}=\frac{\exp\left(\frac{Min(r_{ij}^{k})}{r_{ij}^{k}}\right)}{\sum_{i=1}^{m}\exp\left(\frac{Min(r_{ij}^{k})}{r_{ij}^{k}}\right)},\text{ for non-benefit criteria} \tag{10}$$

Step 13: For each expert (k), we multiply their performance rating by the weight. The summation aggregates the weighted performance ratings across all experts. The aggregated performance rating reflects the combined impact of expert judgments on item (i). The weights $(IF)_k$ can represent equal weights (where all experts contribute equally) or performance-based weights (where experts with better track records have more influence.

$$\alpha_{ij}=\sum_{k=1}^{p}\left((IF)_k\cdot(t_{ij}^{k}\right) \tag{11}$$

Step 14: The performance rating of ith alternative impacted by expert weights, w_j denotes weight of j^{th} criterion. In simple terms, the weighted performance rating combines the aggregated performance rating with the weight assigned to each criterion. It helps evaluate alternatives while considering their importance in decision-making.

$$\beta_{ij}=\alpha_{ij}^{1-\sqrt{w_j}} \tag{12}$$

Step 15: This step involves calculating the Performance Score (PSi) for the ith alternative, which is a measure that combines both the arithmetic and geometric means of the weighted performance ratings (β_{ij}) of the ith alternative with respect to the jth criterion. Specifically, β_{ij} represents the weighted performance rating of the ith alternative concerning the jth criterion. To compute PSi, the arithmetic mean of all β_{ij} values for the ith alternative need to be determined which provides a straightforward average. Next, calculation of the geometric mean of these β_{ij} values id determined, which gives a multiplicative average that can highlight the impact of lower ratings more significantly. Finally, PSi is obtained by taking the average of these two means, effectively balancing the linear and multiplicative perspectives of performance ratings. This dual approach ensures a comprehensive evaluation of the alternative's performance across multiple criteria.

$$PS_i=\frac{1}{2}\left(\frac{1}{n}\sum_{j=1}^{n}\beta_{ij}+\left(\prod_{j=1}^{n}\beta_{ij}\right)^{\frac{1}{n}}\right) \tag{13}$$

Step 16: In Step 16, the measure of performance index (PI_i) for each alternative is computed to evaluate and compare the performance of different options. The notation PS_i represents the performance score for the i^{th} alternative. This calculation involves determining the minimum performance score among all alternatives, denoted as $Min\ (PS_i)$. The difference between the performance score of a specific alternative and the minimum performance score is then divided by the minimum performance score. This ratio is multiplied by 100 to convert it into a percentage, providing a normalized index that reflects how much better or worse each alternative performs relative to the least performing option. This method ensures a standardized comparison, highlighting the relative efficiency and effectiveness of each alternative in a clear and quantifiable manner.

$$PI_i=\left(\frac{PS_i-Min(PS_i)}{Min(PS_i)}\right)\times 100 \tag{14}$$

Step 17: The alternatives are ranked according to PI_i ratings. Choose the alternative with highest measure of performance index as the optimal choice.

The suggested HGEDM approach is established through three practical numerical examples to assess its relevance and efficiency in present manufacturing scenario.

3. Illustrations of Numerical Examples

In this segment, the suggested decision making methodology is exemplified with three diverse real-world numerical examples under sub-segments 3.1, 3.2 and 3.3.

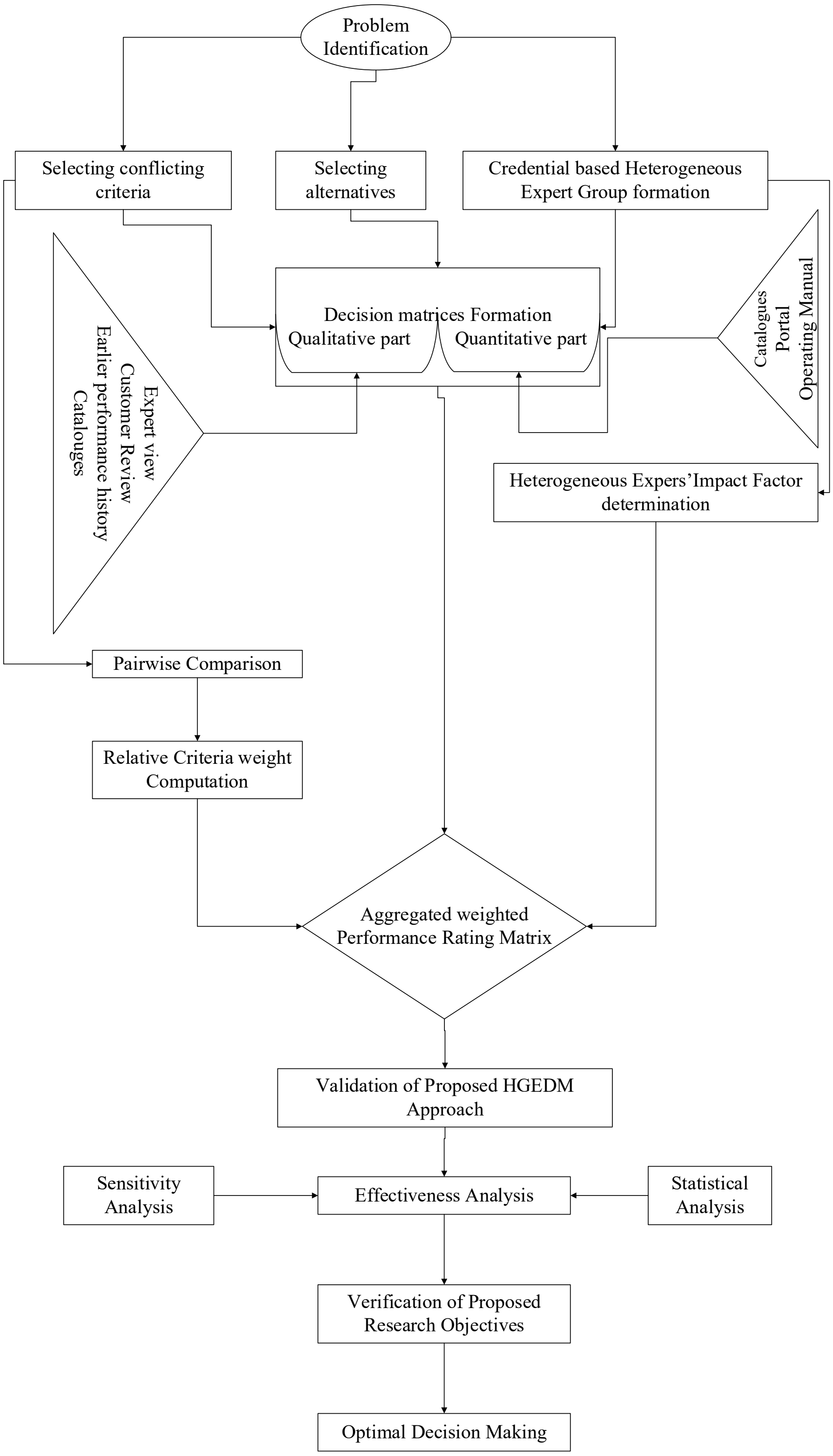

Fig. 1. Flow diagram of the proposed HGEDM approach

An advanced industrial automation training institute in Kolkata, West Bengal, India, is engaged in offering top-notch computer aided manufacturing (CAM) courses and multi-fold enhancement of CNC programming skill development programs. The institute also provides vital technological support to metal working machinery manufacturing industries in the vicinity of the training institute to address ever new manufacturing challenges. Now the training institute is planning to expand the existing state-of-the-art facilities to bring in more sophisticated exposures to diverse CNC machining skills to trainees, engineers and industry personnel in ensuring industry-ready careers in most modern digital manufacturing areas.

With a view to developing competitive advantages for trainees in world-class computerized manufacturing scenario the institute's management has decided to purchase most suitable heavy-duty wood working gantry type 3-axes CNC router machine, 3-axes CNC horizontal lathe machine and CNC wire cut EDM machine. In order to assess and select the best alternatives, the institute's management has constituted a decision-making group comprising four diverse experts. In this evaluation process a few reputed CNC machine tools manufacturers are chosen by diverse expert group such as Jyoti automations, Tirupati machine tools, JAEWOO machine tools, Marshall, DMG Mori, Okuma, Hyundai, Philips and Mazak etc. For evaluation and selection process, here heterogeneous experts are denoted by HGE1……HGE4 respectively. The academic credentials and professional responsibilities of the experts are detailed in Table 2. In this selection problem all subjective attributes are given with triangular fuzzy numbers (TFN) with respect to linguistic values (LV). LV-TFN explanation is shown in Table 3. The flow diagram portraying the suggested HGEDM approach is represented in Fig. 1. It outlines the roadmap toward optimal decision-making, depicting the sequential steps involved in the proposed methodology.

Table 2
Heterogeneous Expert group

Expert	Academic qualification	Experience	Gender	Capacity	Job responsibility
HGE1	Post graduate degree in Production Engineering	More than 20 years	Female	Assistant Manager	Responsible for process planning, designing and scheduling of tool room
HGE2	Bachelor's degree in Mechanical Engineering	More than 17 years	Male	Tool room Manager	Prepare and implement procedure for mold cleaning, loading, unloading, and inspection
HGE3	Degree in Tool-die Engineering	More than 13 years	Male	Tool room Supervisor	Allocating, scheduling and checking maintenance as per routine schedule of production in tool room
HGE4	Diploma in CAD-CAM	More than 10 years	Female	Senior CNC Technician	To set up different types of CNC equipment for their work and to produce precision parts using blueprints or computer-aided design files

Table 3
LV and TFN for various parameters related to CNC machines

LV with abbreviation for CNC machine performance ratings	TFN
outstanding (O)	(8, 9, 10)
excellent (E)	(7, 8, 9)
very good (VG)	(6, 7, 8)
good (G)	(5, 6, 7)
medium (M)	(4, 5, 6)
fair (F)	(3, 4, 5)
satisfactory (S)	(2, 3, 4)
poor (P)	(1, 2, 3)
very poor (VP)	(0, 1, 2)
LV with abbreviation for criteria weights and relative expert weights	
extremely high (EH)	(8, 9, 10)
very high (VH)	(7, 8, 9)
high (H)	(6, 7, 8)
slightly high (SH)	(5, 6, 7)
medium (M)	(4, 5, 6)
slightly low (SL)	(3, 4, 5)
low (L)	(2, 3, 4)
very low (VL)	(1, 2, 3)
extremely low (EL)	(0, 1, 2)

3.1 Numerical Example 1

In this sub-section the suggested HGEDM approach is exemplified with a numerical example on heavy duty gantry type 3-axes CNC wood working router. A CNC wood working router is designed to automate cutting, carving and shaping processes according to design specifications. It uses a rotating router bit which is programmed to execute exact movements over the work piece fitted to a movable table, along the X, Y, and Z axes. The Gantry is a structural part that supports the router head holding the router bit and provides stability throughout operation. The CNC wood routers can handle a wide range of materials including wood, plastics, composites and foams. Some applications of CNC wood router are furniture making, artistic carvings, cabinetry, crafts and art etc. To evaluate and select the best CNC wood router, the relevant conflicting criteria with codes and their nature are presented in Table 4.

Step 1: After determining all relevant criteria and competitive alternatives, the diverse experts (HGE1……HGE4) constructs decision matrices as shown in Table 5-Table 8, according to the proposed methodology (Step-1). The performance ratings of alternatives are assigned with LV against qualitative attributes as defined in Table 3.

Step 2: The pair-wise criteria comparison matrix assessed by HGE1 is constructed based on the proposed methodology (Step 2) and is presented in Table 9. Geometric mean of pairwise comparison for each criterion is calculated. The priority vector pv_j for each criteria with respect to expert 1 (HGE1) is computed in accordance with Eq.(1) and is shown in Table 9. For example, pv_j= (2.4844/11.9124) =0.1924 and thus the remaining values of pv_j for HGE2, HGE3 and HGE4 are calculated in similar way. Thus, remaining pairwise criteria comparison matrices by experts HGE2, HGE3 and HGE4 are constructed similarly.

Table 4

Criteria with codes and nature of criteria for evaluation of alternatives

Criteria	Unit	Code	Characteristics of criteria
Ex.1: Heavy duty Gantry type 3-axes CNC wood router			
Tool travel along X-Y-Z axes	mm	A1	performance oriented
Work table	mm	A2	performance oriented
Average cutting speed	m/min	A3	performance oriented
Spindle motor	kW	A4	performance oriented
Cutting tool diameter	mm	A5	performance oriented
Customer review	--	A6	subjective
Customer support system	--	A7	subjective
Availability of spare parts	--	A8	environment oriented
Energy efficiency	--	A9	environment oriented
Control system	--	A10	performance oriented
Dust pollution effect	--	A11	environment oriented
Toxic effect	--	A12	environment oriented
Ex.2: 3-axes CNC Wire-cut EDM machine			
Average Wire feed rate	mm/min	P1	performance oriented
Wire traverse along U-V-Z axes	mm	P2	performance oriented
Table traverse along X-Y axes	mm	P3	performance oriented
Customer feedback	--	P4	subjective
Flushing system	--	P5	performance oriented
Machining accuracy	--	P6	threshold or range
Dielectric cooling capacity	--	P7	performance oriented
Maintainability	--	P8	performance oriented
Cutting efficiency	--	P9	performance oriented
Spares availability	--	P10	environment oriented
Energy consumption	--	P11	environment oriented
Toxic effect	--	P12	environment oriented
Ex.3: Horizontal 3-axes CNC Lathe machine			
Rapid tool traverse along X-axis	mm/min	C1	performance oriented
Rapid tool traverse along Z-axis	mm/min	C2	performance oriented
max. spindle movement along X-axis	mm	C3	performance oriented
max. spindle movement along Y-axis	mm	C4	performance oriented
max. spindle movement along Z-axis	mm	C5	performance oriented
Swing over bed	mm	C6	performance oriented
Max bar capacity	mm	C7	performance oriented
Customer review	--	C8	subjective
Cooling system	--	C9	performance oriented
Position repeatability	--	C10	threshold or range
Energy consumption	--	C11	environment oriented
Toxic effect	--	C12	environment oriented

Step 3: The criteria weight is computed in accordance with Eq.(2). For example, criteria weight Wj for C1= [(0.1924+0.1976+0.2095+0.2041)/4]=0.2009. Thus, remaining criteria weights are calculated and are presented in Table 10.

Step 4: The relative weight of experts is assigned in linguistic variables as assessed by expert 1 (HGE1) based on expert's credential (Table 2) and are shown in Table 11. The relative expert weights assessed by other experts are formed in similar manner.

Step 5: The relative weight of experts in linguistic variables as assessed by HGE1 is expressed in triangular fuzzy number and are shown in Table 12. The remaining expert weight matrices by mutual assessment in fuzzy number are also formed in similar manner.

Step 6: Aggregate expert weights in fuzzy number are calculated according to Eq.(3) and is shown in Table 13.

Step 7: Aggregate expert weight values in fuzzy number is converted into crisp number in accordance with Eq.(4) and are presented in Table 14. For example, the first element in table 14 is calculated as (6.75+7.75+8.5)/3=7.66. Thus the reaming crisp numbers are calculated in similar way.

Step 8: The normalized value of expert weight is computed in accordance with Eq.(5) and are presented in Table 15. For example, first element in the Table 15 is obtained as (7.66/24.46)=0.313 and remaining are calculated similarly.

Step 9: The Effective Aggregate value of respective experts are computed using Eq.(6) and are presented in Table 15.

Step 10: The impact factor (IF) of heterogeneous experts are calculated in accordance with Eq.(7) and are presented in Table 15. For instance, (IF) of HGE1 is calculated as (2.552/11.017)=0.232 and the reaming are calculated similarly.

Table 5

Decision matrix by HGE1

Alternatives	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)
NR115	1300×2500×200	1440× 3040	25	4.5	10	3.9	G	H	M	M	H	M
LX 1325	1400×1250×150	1400×3000	20	6	15	4.1	M	SH	SH	G	M	SH
LX1212	1200×1200×200	1400×2400	20	4	12	4.3	VG	M	SL	M	SH	L
RX1325	1400×1250×150	1300×2300	18	5	15	4	F	SH	H	G	M	SL
LX1530	1400×1250×150	1450×2200	18	6	15	4.2	G	H	SL	M	SL	H
ST1325	1350×1250×250	1300×2500	18	4	15	4.3	G	M	SH	VG	SH	SL
GX-1325V	1300×2500×300	1300×2250	22	6.5	20	4.1	F	H	M	M	L	SL
KCPSR1	1400×1250×150	1400×3000	18	4.5	18	4.2	G	SH	SH	F	M	H
DL1325	1400×1250×150	1400×2800	18	4	15	4	VG	H	M	M	SH	SL
K-1325D	1300×2500×220	1300×2700	18	6	10	4	M	M	SL	G	H	M
AR1325	1300×2500×300	1350×2500	20	5.5	15	4.1	G	M	M	F	SH	SL

Table 6

Decision matrix by HGE2

Alternatives	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)
NR115	1300×2500×200	1440× 3040	25	4.5	10	3.9	G	SH	M	F	M	H
LX 1325	1400×1250×150	1400×3000	20	6	15	4.1	G	H	M	M	SH	SH
LX1212	1200×1200×200	1400×2400	20	4	12	4.3	F	M	SL	G	H	L
RX1325	1400×1250×150	1300×2300	18	5	15	4	G	M	M	F	SH	H
LX1530	1400×1250×150	1450×2200	18	6	15	4.2	F	H	SL	M	SL	SL
ST1325	1350×1250×250	1300×2500	18	4	15	4.3	G	M	SH	M	SH	M
GX-1325V	1300×2500×300	1300×2250	22	6.5	20	4.1	F	H	M	G	L	SL
KCPSR1	1400×1250×150	1400×3000	18	4.5	18	4.2	VG	SH	SH	F	SH	H
DL1325	1400×1250×150	1400×2800	18	4	15	4	F	M	SL	M	L	SL
K-1325D	1300×2500×220	1300×2700	18	6	10	4	G	SH	M	G	SH	M
AR1325	1300×2500×300	1350×2500	20	5.5	15	4.1	VG	H	SL	F	SL	H

Step 11: Defuzzification of performance rating of alternatives in decision matrix by HGE1 is performed using Eq. (8) and is shown in Table 16. Others decision matrices by respective experts are formed in similar way.

Step 12: The normalized value (t_{ij}^{k}) of crisp performance rating of alternatives as assessed by HGE1 is calculated for benefit criteria and non-benefit criteria using Eq.(9) and Eq.(10) and are presented in Table 17. Similarly others normalized matrices of crisp performance rating of alternatives as assessed by HGE2, HGE3 and HGE4 are also constructed in similar manner.

Step 13: The aggregate performance rating of alternatives is computed using Eq.(11) and is presented in Table 18.

Step 14: The aggregate weighted performance rating of alternatives is computed in accordance with Table 18 and Eq.(12). The weighted ratings of alternatives are presented in Table 19. For example, β_{ij}=[0.1031^{1-sqrt(0.2009)}]=0.2854 is the first element of Table 19 and similarly reaming are calculated.

Step 15: The performance score for alternative is computed using Eq.(13) and are presented in Table 20. For example, the performance score for alternative NR115 is calculated as: (0.2003+0.1939)/2 =0.1971 and similarly remaining performance scores of respective alternatives are calculated.

Table 7

Decision matrix by HGE3

Alternatives	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)
NR115	1300×2500×200	1440× 3040	25	4.5	10	3.9	VG	M	M	G	L	SL
LX 1325	1400×1250×150	1400×3000	20	6	15	4.1	F	SH	SH	F	M	M
LX1212	1200×1200×200	1400×2400	20	4	12	4.3	G	H	SL	G	SL	SL
RX1325	1400×1250×150	1300×2300	18	5	15	4	VG	SH	M	M	SH	H
LX1530	1400×1250×150	1450×2200	18	6	15	4.2	F	H	SL	G	L	SL
ST1325	1350×1250×250	1300×2500	18	4	15	4.3	G	M	L	F	M	SL
GX-1325V	1300×2500×300	1300×2250	22	6.5	20	4.1	VG	H	M	M	SH	M
KCPSR1	1400×1250×150	1400×3000	18	4.5	18	4.2	G	SH	M	F	M	H
DL1325	1400×1250×150	1400×2800	18	4	15	4	VG	M	SL	F	L	M
K-1325D	1300×2500×220	1300×2700	18	6	10	4	G	SH	M	M	H	L
AR1325	1300×2500×300	1350×2500	20	5.5	15	4.1	F	H	L	F	L	SL

Table 8

Decision matrix by HGE4

Alternatives	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)
NR115	1300×2500×200	1440× 3040	25	4.5	10	3.9	VG	H	M	M	SL	SL
LX 1325	1400×1250×150	1400×3000	20	6	15	4.1	G	SH	SH	F	L	H
LX1212	1200×1200×200	1400×2400	20	4	12	4.3	G	M	SL	M	L	M
RX1325	1400×1250×150	1300×2300	18	5	15	4	F	SH	H	M	M	SL
LX1530	1400×1250×150	1450×2200	18	6	15	4.2	G	H	SL	G	SH	H
ST1325	1350×1250×250	1300×2500	18	4	15	4.3	VG	M	SH	F	L	SL
GX-1325V	1300×2500×300	1300×2250	22	6.5	20	4.1	F	H	M	M	M	M
KCPSR1	1400×1250×150	1400×3000	18	4.5	18	4.2	G	SH	SH	G	M	H
DL1325	1400×1250×150	1400×2800	18	4	15	4	F	H	M	F	SH	SL
K-1325D	1300×2500×220	1300×2700	18	6	10	4	M	M	SL	G	H	H
AR1325	1300×2500×300	1350×2500	20	5.5	15	4.1	G	M	M	F	M	SL

Table 9

Pairwise comparison matrix by HGE1

HGE1	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)	GM	P_{vj}
A1	1.000	3.000	1.000	2.000	2.000	3.000	2.000	4.000	4.000	3.000	4.000	4.000	2.4844	0.1924
A2	0.333	1.000	3.000	1.500	1.500	1.000	1.500	0.750	0.750	1.000	0.750	0.750	1.0055	0.0779
A3	1.000	0.333	1.000	2.000	2.000	1.333	2.000	1.000	1.000	1.333	1.000	1.000	1.1385	0.0882
A4	0.500	0.667	0.500	1.000	1.000	0.667	1.000	0.500	0.500	0.667	0.500	0.500	0.6389	0.0495
A5	0.500	0.667	0.500	1.000	1.000	0.667	1.000	0.500	0.500	0.667	0.500	0.500	0.6389	0.0495
A6	0.333	1.000	0.750	1.500	1.500	1.000	1.500	0.750	0.750	1.000	0.750	0.750	0.8958	0.0694
A7	0.500	0.667	0.500	1.000	1.000	0.667	1.000	0.500	0.500	0.667	0.500	0.500	0.6389	0.0495
A8	0.250	1.333	1.000	2.000	2.000	1.333	2.000	1.000	1.000	1.333	1.000	1.000	1.1385	0.0882
A9	0.250	1.333	1.000	2.000	2.000	1.333	2.000	1.000	1.000	1.333	1.000	1.000	1.1385	0.0882
A10	0.333	1.000	0.750	1.500	1.500	1.000	1.500	1.000	0.750	1.000	0.750	0.750	0.9175	0.0711
A11	0.250	1.333	1.000	2.000	2.000	1.333	2.000	1.000	1.000	1.333	1.000	1.000	1.1385	0.0882
A12	0.250	1.333	1.000	2.000	2.000	1.333	2.000	1.000	1.000	1.333	1.000	1.000	1.1385	0.0882
							Sum						12.9124	1.000

Table 10

Criteria weight computation

	HGE1	HGE2	HGE3	HGE4	
Criteria	P_{vj}	P_{vj}	P_{vj}	P_{vj}	W_j
A1	0.1924	0.1976	0.2095	0.2041	0.2009
A2	0.0779	0.0559	0.0706	0.0525	0.0642
A3	0.0882	0.0559	0.0706	0.0935	0.0771
A4	0.0495	0.0765	0.0897	0.0935	0.0773
A5	0.0495	0.0559	0.0897	0.0754	0.0676
A6	0.0694	0.0996	0.0504	0.0525	0.0680
A7	0.0495	0.0733	0.0504	0.0853	0.0646
A8	0.0882	0.0784	0.0897	0.0525	0.0772
A9	0.0882	0.0559	0.0706	0.0525	0.0668
A10	0.0711	0.0941	0.0876	0.0711	0.0810
A11	0.0882	0.0784	0.0706	0.0935	0.0827
A12	0.0882	0.0784	0.0504	0.0736	0.0726

Table 11
Relative expert weights matrix in LV as assessed by HGE1

Nature of Experts	factor 1	factor 2	factor 3	factor 4
HGE1	E	VG	M	G
HGE2	VG	E	G	M
HGE3	E	VG	E	M
HGE4	M	G	E	E

Table 12
Expert weight matrix in TFN as assessed by HGE1

Expert	factor 1	factor 2	factor 3	factor 4
HGE1	(7,8,9)	(6,7,8)	(4,5,6)	(5,6,7)
HGE2	(6,7,8)	(4,5,6)	(5,6,7)	(4,5,6)
HGE3	(7,8,9)	(6,7,8)	(7,8,9)	(4,5,6)
HGE4	(4,5,6)	(5,6,7)	(7,8,9)	(7,8,9)

Table 13
Aggregate expert weight matrix in fuzzy number

Expert	factor 1	factor 2	factor 3	factor 4
HGE1	(6.75,7.75,8.5)	(5.75,6.75,7.75)	(3.5,4.5,5.5)	(4.75,5.75,6.75)
HGE2	(6.5,7.5,8.5)	(4.25,5.25,6.25)	(4.75,5.75,6.75)	(5,6,7)
HGE3	(7.25,8.25,9.25)	(6,7,8)	(6.25,7.25,8.25)	(4.75,5.75,6.75)
HGE4	(5.25,6.25,7.25)	(6,7,8)	(7.25,8.25,9.25)	(4.75,5.75,6.75)

Table 14
Defuzzification matrix of the aggregate expert weights

Expert	factor 1	factor 2	factor 3	factor 4
HGE1	7.66	6.75	3.37	5.75
HGE2	**2.3**	5.25	5.75	6
HGE3	8.25	9	7.5	5.75
HGE4	6.25	7	8.25	5.75
Sum	24.46	28	24.87	23.25

Table 15
Normalized expert weight matrix

Nature of Experts	factor 1	factor 2	factor 3	factor 4	Sum	Effective Aggregate value	Impact Factor of Experts
HGE1	0.313	0.241	0.136	0.247	0.937	2.552	0.232
HGE2	0.094	0.188	0.231	0.258	0.771	2.161	0.196
HGE3	0.337	0.321	0.302	0.247	1.208	3.345	0.304
HGE4	0.256	0.250	0.332	0.247	1.085	2.958	0.268
			Sum			11.017	1.000

Table 16
Decision matrix by HGE1 into crisp number

Alternatives	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)
NR115	650000000	4377600	25	4.5	10	3.9	6	7	5	5	7	5
LX 1325	262500000	3360000	20	6	15	4.1	5	6	6	6	5	6
LX1212	288000000	3360000	20	4	12	4.3	7	5	6	5	6	3
RX1325	262500000	2990000	18	5	15	4	4	6	7	6	5	4
LX1530	262500000	3190000	18	6	15	4.2	6	7	4	5	4	7
ST1325	421875000	3250000	18	4	15	4.3	6	5	6	7	6	4
GX-1325V	975000000	2925000	22	6.5	20	4.1	4	7	5	5	3	4
KCPSR1	262500000	2990000	18	4.5	18	4.2	6	6	6	4	5	7
DL1325	262500000	3920000	18	4	15	4	7	7	5	5	6	4
K-1325D	715000000	3510000	18	6	10	4	5	5	4	6	7	5
AR1325	975000000	3375000	20	5.5	15	4.1	6	5	5	4	6	4
max	975000000	4377600	25	6.5	20	4.3	7	7	7	7	7	7
min	262500000	2925000	18	4	10	3.9	4	5	4	4	3	3

Table 17
Normalized matrix of crisp performance rating of alternatives as assessed by HGE1

Alternatives	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)
NR115	0.1031	0.1135	0.1126	0.0822	0.0717	0.0866	0.0948	0.1041	0.0856	0.0868	0.0769	0.0841
LX 1325	0.0693	0.0900	0.0922	0.1036	0.0920	0.0907	0.0822	0.0902	0.0988	0.1001	0.0913	0.0761
LX1212	0.0711	0.0900	0.0922	0.0761	0.0792	0.0950	0.1094	0.0782	0.0988	0.0868	0.0826	0.1255
RX1325	0.0693	0.0827	0.0851	0.0888	0.0920	0.0886	0.0713	0.0902	0.1139	0.1001	0.0913	0.0977
LX1530	0.0693	0.0865	0.0851	0.1036	0.0920	0.0928	0.0948	0.1041	0.0742	0.0868	0.1060	0.0709
ST1325	0.0816	0.0877	0.0851	0.0761	0.0920	0.0950	0.0948	0.0782	0.0988	0.1155	0.0826	0.0977
GX-1325V	0.1439	0.0814	0.0999	0.1118	0.1182	0.0907	0.0713	0.1041	0.0856	0.0868	0.1361	0.0977
KCPSR1	0.0693	0.0827	0.0851	0.0822	0.1069	0.0928	0.0948	0.0902	0.0988	0.0752	0.0913	0.0709
DL1325	0.0693	0.1022	0.0851	0.0761	0.0920	0.0886	0.1094	0.1041	0.0856	0.0868	0.0826	0.0977
K-1325D	0.1102	0.0931	0.0851	0.1036	0.0717	0.0886	0.0822	0.0782	0.0742	0.1001	0.0769	0.0841
AR1325	0.1439	0.0903	0.0922	0.0959	0.0920	0.0907	0.0948	0.0782	0.0856	0.0752	0.0826	0.0977

Table 18
Aggregated performance rating matrix

Alternatives	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)
NR115	0.1031	0.1135	0.1126	0.0822	0.0717	0.0866	0.1029	0.0932	0.0916	0.0931	0.2303	0.0927
LX 1325	0.0693	0.0900	0.0922	0.1036	0.0920	0.0907	0.0848	0.0926	0.1037	0.0858	0.2148	0.0777
LX1212	0.0711	0.0900	0.0922	0.0761	0.0792	0.0950	0.0933	0.0857	0.0841	0.0992	0.2071	0.1083
RX1325	0.0693	0.0827	0.0851	0.0888	0.0920	0.0886	0.0871	0.0876	0.1059	0.0911	0.2018	0.0877
LX1530	0.0693	0.0865	0.0851	0.1036	0.0920	0.0928	0.0830	0.1037	0.0784	0.1004	0.2560	0.0850
ST1325	0.0816	0.0877	0.0851	0.0761	0.0920	0.0950	0.0986	0.0779	0.0931	0.0893	0.2127	0.0986
GX-1325V	0.1439	0.0814	0.0999	0.1118	0.1182	0.0907	0.0824	0.1037	0.0916	0.0940	0.3012	0.0920
KCPSR1	0.0693	0.0827	0.0851	0.0822	0.1069	0.0928	0.0976	0.0899	0.1015	0.0855	0.2040	0.0714
DL1325	0.0693	0.1022	0.0851	0.0761	0.0920	0.0886	0.0912	0.0909	0.0842	0.0827	0.3007	0.0973
K-1325D	0.1102	0.0931	0.0851	0.1036	0.0717	0.0886	0.0883	0.0839	0.0858	0.1016	0.1935	0.0936
AR1325	0.1439	0.0903	0.0922	0.0959	0.0920	0.0907	0.0907	0.0908	0.0803	0.0773	0.2527	0.0958

Table 19
Aggregate weighted performance rating matrix

Alternatives	A1 (+)	A2 (+)	A3 (+)	A4 (+)	A5 (+)	A6 (+)	A7 (+)	A8 (+)	A9 (+)	A10 (+)	A11 (-)	A12 (-)
NR115	0.2854	0.1970	0.2065	0.1647	0.1423	0.1638	0.1835	0.1803	0.1699	0.1830	0.3513	0.1759
LX 1325	0.2292	0.1656	0.1787	0.1945	0.1712	0.1695	0.1588	0.1794	0.1862	0.1725	0.3342	0.1546
LX1212	0.2325	0.1656	0.1787	0.1558	0.1532	0.1755	0.1705	0.1696	0.1594	0.1914	0.3257	0.1971
RX1325	0.2292	0.1555	0.1687	0.1741	0.1712	0.1667	0.1620	0.1723	0.1892	0.1802	0.3197	0.1690
LX1530	0.2292	0.1609	0.1687	0.1945	0.1712	0.1725	0.1563	0.1947	0.1514	0.1930	0.3788	0.1652
ST1325	0.2508	0.1625	0.1687	0.1558	0.1712	0.1755	0.1777	0.1584	0.1719	0.1776	0.3320	0.1840
GX-1325V	0.3430	0.1538	0.1894	0.2057	0.2060	0.1695	0.1554	0.1947	0.1699	0.1843	0.4253	0.1750
KCPSR1	0.2292	0.1555	0.1687	0.1647	0.1913	0.1725	0.1763	0.1756	0.1834	0.1721	0.3222	0.1454
DL1325	0.2292	0.1822	0.1687	0.1558	0.1712	0.1667	0.1677	0.1770	0.1596	0.1681	0.4248	0.1823
K-1325D	0.2961	0.1699	0.1687	0.1945	0.1423	0.1667	0.1637	0.1670	0.1618	0.1947	0.3103	0.1773
AR1325	0.3430	0.1660	0.1787	0.1840	0.1712	0.1695	0.1669	0.1768	0.1541	0.1601	0.3753	0.1803

Step 16: The measure performance index is calculated using Eq.(14) and is shown in Table 20. For instance, the performance score for alternative NR115 is calculated according to Eq.14 as: [(0.1971-0.1860)/0.1860]*100=5.9865 and similarly remaining performance indices of respective alternatives are calculated.

Step 17: Based on performance index (PI) measures of alternatives, rank calculations are made accordingly and are shown in Table 20. The alternative with highest PI measure is considered the optimal choice.

Table 20
Performance score of alternatives

Alternatives	A M	GM	Performance score	Performance index	Rank
NR115	0.2003	0.1939	0.1971	5.9865	3
LX 1325	0.1912	0.1869	0.1890	1.6440	7
LX1212	0.1896	0.1853	0.1874	0.7771	9
RX1325	0.1881	0.1843	0.1862	0.1240	10
LX1530	0.1947	0.1883	0.1915	2.9683	5
ST1325	0.1905	0.1858	0.1881	1.1637	8
GX-1325V	0.2143	0.2035	0.2089	12.3390	1
KCPSR1	0.1881	0.1839	0.1860	0.0000	11
DL1325	0.1961	0.1878	0.1920	3.2148	4
K-1325D	0.1928	0.1872	0.1900	2.1550	6
AR1325	0.2022	0.1930	0.1976	6.2477	2
	min		0.1860		

3.2 Numerical Example 2

In this sub-segment, the suggested approach is exemplified with a research problem on 3-axes CNC Wire-cut EDM machines. The Wire EDM machining is an electro thermal manufacturing practice that employs electric discharges to remove material from a work piece submerged into dielectric fluid. This method enhances the conventional EDM process and is compatible with almost all conductive materials, enabling the formation of intricate designs and shapes. The machining process generates fine chips and exact cut lines by melting or vaporizing the material, instead of cutting it mechanically as in traditional machining process. After determining all relevant criteria and chosen alternatives, the heterogeneous expert HGE1 constructs a decision matrix as presented in Table 21 using the proposed methodology (Step 1). The other decision matrices by HGE2, HGE3 and HGE4 are formed in similar manner. The steps are comparable to Ex.1 to compute the rank order of chosen alternatives.

Table 21
Decision matrix by HGE1 in Ex.2

Alternatives	P1 (+)	P2 (+)	P3 (+)	P4 (+)	P5 (+)	P6 (+)	P7 (+)	P8 (+)	P9 (+)	P10 (+)	P11 (-)	P12 (-)
G32F	900	60 × 60 × 240	360 × 250	4.1	G	VH	H	H	SL	H	M	M
eNOVA OS	800	80 × 80 × 200	361 × 250	4	M	H	VH	M	M	SH	L	L
SMART F43	900	80 × 80 × 150	362 × 250	4	G	SH	H	H	H	M	M	M
Ultima OF	850	80 × 80 × 250	320 × 220	4.2	F	H	SL	H	SL	SH	H	L
GE-32S	800	70 × 70 × 220	320 × 220	4.3	S	SH	H	M	M	H	M	M
GE-43F	900	70 × 70 × 210	350 × 250	4.1	G	VH	VH	H	H	M	SL	L
AU-3iA	950	80× 80 × 210	350× 250	4.1	S	SH	H	M	H	SL	M	M
AL-400SA	850	70 × 70 × 220	350 × 250	4.2	G	VH	VH	H	SL	SH	L	H
GA-43	850	70 × 70 × 220	400 × 250	4.2	F	H	H	SH	H	H	M	H
AP-4030A	900	60 × 60 × 220	400 × 300	3.9	M	SH	M	M	SL	M	L	M
ZNC-30S	850	80× 80 × 210	300 × 200	4	G	H	H	SH	SL	SH	M	SL

3.3 Numerical Example 3

In this sub-section the suggested approach is exemplified with a numerical example on 3-axes CNC Lathe machines. A 3-axes horizontal CNC lathe machine is a cutting-edge, versatile machine, equipped with various cutting capacities. The entire system is enclosed to ensure operator's safety. The CNC lathe machine allows a cylindrical work piece to rotate while a fixed cutting tool is fed into it, removing material to achieve a production-grade surface finish in a cost-effective manner. Advanced manufacturing industries favor this CNC machine tool because it efficiently removes large quantities of material while maintaining a consistent and customized finished product. After determining all relevant criteria and chosen alternatives, the HGE 1 forms a decision matrix as shown in Table 22 using proposed methodology (Step 1). The other decision matrices by HGE2, HGE3 and HGE4 are formed in similar manner. The rank positions of alternatives are calculated according to the proposed algorithm as illustrated in Ex.1 & Ex.2 respectively.

Table 22
Decision matrix by HGE1 in Ex.3

Alternatives	C1 (+)	C2 (+)	C3 (+)	C4 (+)	C5 (+)	C6 (+)	C7 (+)	C8 (+)	C9 (+)	C10 (+)	C11 (-)	C12 (-)
NLX2000	20	18	260	100	590	370	60	4.3	G	VH	M	L
TCP-H-300L	18	18	200	80	550	400	50	4.1	F	H	SL	SL
LB3000 EXIII	18	15	250	80	550	410	60	4.4	S	SH	L	M
CK 6100	17	15	250	100	540	400	55	3.9	G	H	M	SL
ST 225	22	22	220	80	450	430	45	4.1	F	SH	L	M
ACE 5075	18	14	230	100	490	380	70	4.2	G	VH	SL	L
Art 350s+	22	20	180	90	420	400	45	4.2	S	SH	M	SL
SL-14D	24	24	160	100	380	400	45	4.1	G	VH	L	M
DX 60	24	24	230	100	490	360	55	4.2	F	H	SL	SL
Turn 35 U	22	20	230	100	490	380	60	4	F	SH	M	L
SBL GT-100	24	24	200	120	480	400	42	4	G	H	SL	M

4. Results and Discussions

An in-depth analysis and discussion of the results are conducted to determine efficacy, consistency, and suitability of the suggested HGEDM approach under given industrial context.

4.1 Result analysis of Numerical Example 1

In accordance with the suggested HGEDM approach, the highest PI measure corresponds to the best alternative and the lowest PI measure is the poorest one. Table 20 indicates that the alternative GX-1325V has the highest PI measure (12.3390) and the alternative KCPSR1 has lowest PI measure (0.0000). Based on the proposed approach, the CNC router model GX-1325V emerges as the best alternative whereas KCPSR1 appears to be the least favorable one among the selected alternatives. To validate the suggested approach, a few well established approaches such as SAW, GRA, COPRAS and TOPSIS are recommended to calculate corresponding ranking orders and the results are shown in Table 23. A comparison of the ranking orders across the different approaches is presented in Fig. 2 to show the close alignment of the rank places with each other.

Table 23 and Fig. 2 show that alternative GX-1325V holds the top-ranked position consistently both by the proposed approach and by well-established approaches. The alternative AR1325 is nearly consistent and ranks position 2 in similar way. While the rank places of other alternatives shown in Table 23 obtained from well-established approaches show slight to moderate deviations from those obtained using the proposed approach. For example, the alternative NR115 holds rank 3 three times, rank 2 once, and rank 4 once, as shown in Fig. 2. Given that the primary objective of the industrial automation training institute is to select the best alternative, the diverse group of experts has determined that the proposed approach stands out as the most effective option for such type of selection.

Table 23

Validation of the suggested HGEDM approach by well-established approaches

	Proposed approach		TOPSIS		SAW		GRA		COPRAS	
Alternatives	Performance index	Rank	Relative closeness	Rank	Composite score	Rank	GR grade	Rank	Quantitative utility	Rank
NR115	5.9865	3	0.4577	4	2.4952	3	0.0684	3	97.2593	2
LX 1325	1.6440	7	0.3007	7	2.3946	4	0.0678	6	95.4059	4
LX1212	0.7771	9	0.2834	9	2.2752	9	0.0677	8	93.2629	8
RX1325	0.1240	10	0.2602	11	2.2576	10	0.0676	9	91.9306	10
LX1530	2.9683	5	0.4000	5	2.3564	5	0.0671	11	92.5831	9
ST1325	1.1637	8	0.3000	8	2.2862	8	0.0678	7	94.4363	6
GX-1325V	12.3390	1	0.7518	1	2.5719	1	0.0695	1	100.0000	1
KCPSR1	0.0000	11	0.2741	10	2.2569	11	0.0676	10	90.1644	11
DL1325	3.2148	4	0.4732	3	2.3530	6	0.0682	4	94.6493	5
K-1325D	2.1550	6	0.3753	6	2.3130	7	0.0680	5	93.3818	7
AR1325	6.2477	2	0.5998	2	2.5260	2	0.0687	2	96.9056	3

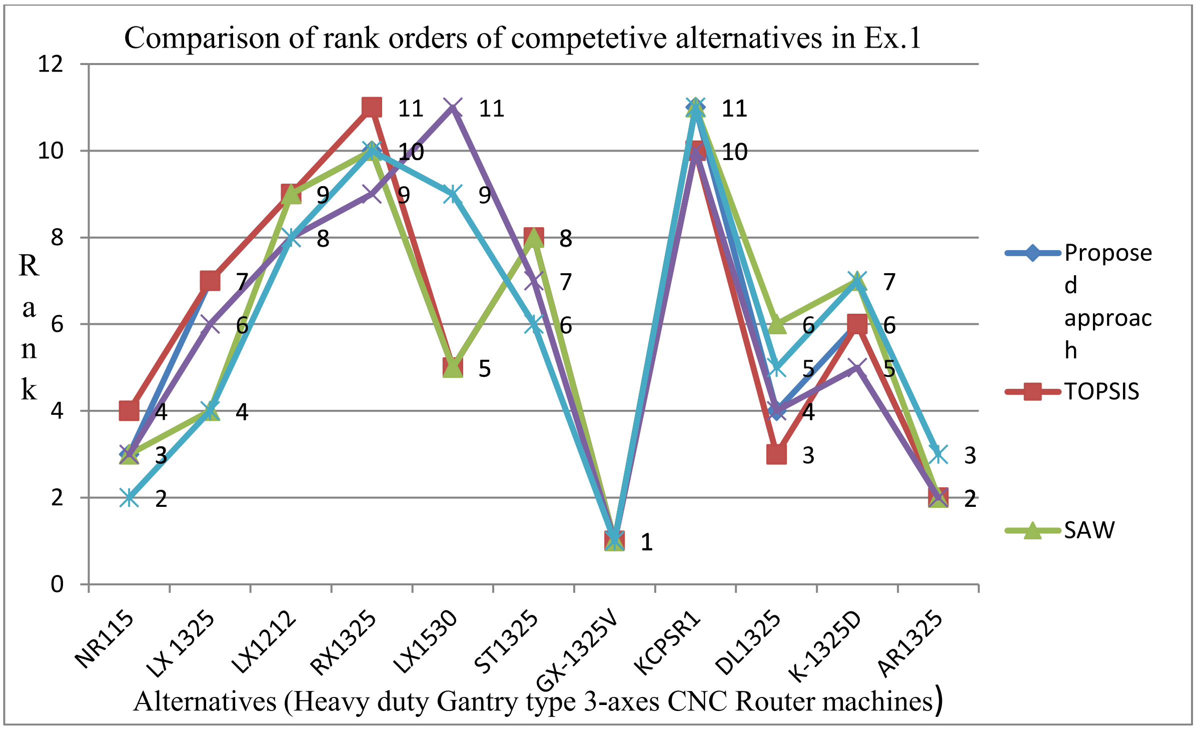

Fig. 2. Comparison of rank orders of alternatives

4.1.1 Sensitivity analysis

In this proposed approach, sensitivity analysis is employed to investigate the extent of rank reversal as the decision-making attitude varies from 0.0 to 1.0. To keep it concise, the analysis is restricted to the top two ranked alternatives only. To perform sensitivity analysis, the machine selection index (*MSI*) is calculated using the mathematical expression: $MSI = [\alpha w_1 + (1-\alpha)$

w_2], where w_1 and w_2 represent the relative performance weights based on summation of positive criteria and cost criteria respectively. Decision making attitude is symbolized by α. Based on MSI values, the corresponding rank calculations for the alternatives are made in the proposed HGEDM approach. Table 24 and Fig.3 show that the top-ranked alternative GX-1325V has two instances of rank (R) reversal: R1 (obtained from proposed approach) to R2 and R2 to R1 corresponding to changes in α at 0.0 and 0.1 respectively. The second-ranked alternative AR1325 experiences only three instances of rank reversal: R2 (Obtained from proposed approach) R3, R3 to R2 and from R2 to R3 corresponding to changes in α at 0.0, 0.3 and 0.9 respectively. Table 24 clearly shows that rank reversals occur in no more than three instances across the decision making attitudes in the proposed approach.

Table 24

Sensitivity analysis for proposed HGEDM approach

Alternatives	rank	rank	rank	rank	rank	rank	rank	rank	rank	rank	rank
NR115	5	5	4	4	3	3	3	3	3	2	2
LX 1325	8	9	9	9	8	7	7	6	6	5	5
LX1212	6	6	6	7	9	9	10	11	11	11	10
RX1325	9	10	10	10	10	10	11	10	10	9	9
LX1530	4	4	5	5	5	5	4	5	5	6	6
ST1325	7	7	7	6	7	8	8	8	8	8	8
GX-1325V	2	1	1	1	1	1	1	1	1	1	1
KCPSR1	11	11	11	11	11	11	9	9	7	7	7
DL1325	1	2	2	3	4	4	5	7	9	10	11
K-1325D	10	8	8	8	6	6	6	4	4	4	4
AR1325	3	3	3	2	2	2	2	2	2	3	3
	(α=0.0)	(α=0.1)	(α=0.2)	(α=0.3)	(α=0.4)	(α=0.5)	(α=0.6)	(α=0.7)	(α=0.8)	(α=0.9)	(α=1.0)

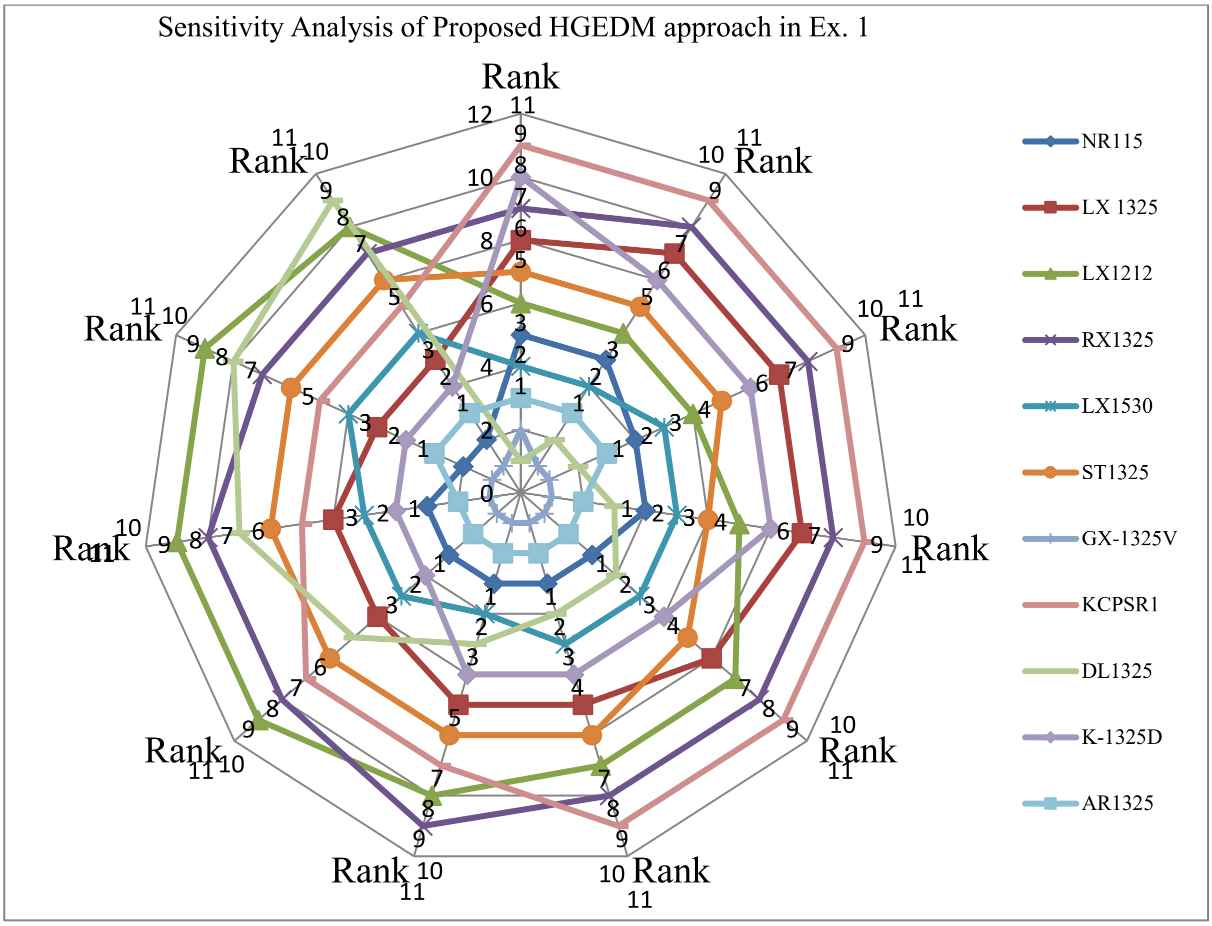

Fig. 3. Sensitivity analysis of the proposed method (Ex.1)

In Table 25, the symbols (√) and (X) are used to represent rank reversal and no rank reversal for alternatives respectively. In the TOPSIS approach, it is observed that rank reversals occur in only two instances: for the top-ranked alternative GX-1325V and the second-ranked alternative AR1325 respectively. In SAW approach, rank reversals occur in only two instances for alternative GX-1325V and three instances for alternative AR1325. In the GRA approach also, rank reversals occur in just two cases for alternative GX-1325V and in three cases for alternative AR1325. In COPRAS approach, the rank reversal trend is same as in SAW approach. The number of rank reversals in the proposed approach closely aligns with those observed in well-established approaches. It indicates that the proposed HGEDM approach maintains consistency with existing models, demonstrating minimal deviations in ranking outcomes. So, the proposed method is is rationally practical, robust and reliable for decision-makers to be considered as an effective decision making aid.

Table 25
Sensitivity analysis across three numerical examples

	Approaches	Alternatives	α= 0.0	α= 0.1	α= 0.2	α= 0.3	α= 0.4	α= 0.5	α= 0.6	α= 0.7	α= 0.8	α= 0.9	α= 1.0	No. of Rank reversals
Numerical Example 1	Proposed HGEDM Approach	GX-1325V	√	√	×	×	×	×	×	×	×	×	×	2
		AR1325	√	×	×	√	×	×	×	×	×	√	×	3
	TOPSIS	GX-1325V	×	×	×	×	×	√	×	×	√	×	×	2
		AR1325	×	×	×	×	√	×	×	×	×	√	×	2
	SAW	GX-1325V	√	√	×	×	×	×	×	×	×	×	×	2
		AR1325	√	×	×	√	×	×	×	×	×	√	×	3
	COPRAS	GX-1325V	√	√	×	×	×	×	×	×	×	×	×	2
		AR1325	√	×	×	√	×	×	×	×	×	√	×	3
	GRA	GX-1325V	√	√	×	×	×	×	×	×	×	×	×	2
		AR1325	√	×	√	×	√	×	×	×	×	×	×	3
Numerical Example 2	Proposed HGEDM Approach	AL-400SA	×	×	×	×	×	×	×	×	×	×	√	1
		GE-43F	√	×	×	√	×	√	×	×	×	×	×	3
	TOPSIS	AL-400SA	√	×	×	×	√	×	×	×	×	×	×	2
		GE-43F	√	×	×	√	√	×	×	×	×	×	×	2
	SAW	AL-400SA	√	×	√	√	×	×	×	×	×	×	×	3
		GE-43F	√	×	×	×	√	√	×	×	×	×	×	3
	COPRAS	AL-400SA	√	×	√	×	×	×	×	×	×	√	×	3
		GE-43F	√	×	×	×	√	√	×	×	×	×	×	3
	GRA	AL-400SA	√	√	×	×	×	×	×	×	×	×	×	2
		GE-43F	√	√	×	×	×	×	√	×	×	×	×	3
Numerical Example 3	Proposed HGEDM Approach	SBL GT-100	√	√	√	×	×	×	×	×	×	×	×	3
		DX 60	√	×	×	√	√	×	×	×	×	×	×	3
	TOPSIS	SBL GT-100	×	×	√	×	√	√	×	×	×	×	×	3
		DX 60	√	×	×	√	×	×	×	×	×	×	×	2
	SAW	SBL GT-100	√	×	√	×	×	×	×	×	×	×	×	2
		DX 60	√	×	×	×	√	√	×	×	×	×	×	3
	COPRAS	SBL GT-100	√	×	√	√	×	×	×	×	×	×	×	3
		DX 60	√	×	×	×	√	√	×	×	×	×	×	3
	GRA	SBL GT-100	√	√	×	√	×	×	×	×	×	×	×	3
		DX 60	√	√	×	×	×	×	√	×	×	×	×	3

4.1.2 Statistical analysis

The authors consider the statistical analysis being crucial for measuring the efficacy of the suggested approach, as it is found inadequacy in the earlier research works according to the literature review. In this research work, Spearman's Rank Correlation Coefficient (SRC), Pearson Correlation Coefficient (PCC) and Sample Correlation Coefficient (SCC) are used to assess the strength and nature of association (positive or negative) between two ranking orders of the respective alternatives derived from pairs of approaches. Table 27 shows that the Spearman's correlation coefficients for the proposed method-TOPSIS, Proposed method-SAW, Proposed method-GRA and Proposed method-COPRAS are 0.98, 0.94, 0.81 and 0.85 respectively. These results indicate a strong positive linear relationship exists between corresponding rank individuals obtained in the pairs of proposed HGEDM approach and well-established approach. To substantiate further the usefulness of the suggested method, the Pearson Correlation Coefficient and the Sample Correlation Coefficient are calculated and the results are shown in Table 27. It shows that the Pearson correlation coefficients are 0.96, 0.92, 0.88 and 0.89 against the pairs of proposed approach and existing one. These values are very close to +1 which indicates a high similarity exists between the proposed HGEDM approach and well-established ones. Similarly, the values of the Sample correlation coefficient shown in Table 27 proves that the suggested HGEDM approach is strong enough to be regarded as an effective decision making aid. The sensitivity and statistical analysis in Ex.1 show that the suggested HGEDM approach is both practical and reliable decision-making technique.

4.2 Result analysis of Numerical Example 2

From Table 26, it is observed that PI measure of alternative AL-400SA is 5.7627 making it the best alternative, while alternative GE-32S has the lowest PI measure (0.0000), making it the poorest one among the competitive alternatives as determined by the suggested HGEDM framework. Validation of the proposed method is done similarly to Ex.1. A comparison of the ranking orders of alternatives between existing approaches and the proposed approach is presented in Fig. 4 to show the closer position of the rank values across the different approaches. Table 26 and Fig. 4 show that alternatives AL-400SA ranks 1 position consistently both by the proposed approach and by well-established approaches. The second-ranked alternative GE-43F is moderately consistent across the approaches. While the rank positions of other alternatives from well existing approaches show slight to reasonable deviations from those obtained using the proposed approach. For example, the alternative SMART F43 is ranked 3 two times, ranks 4 three times as shown in Table 26. Given that the primary objective of the industrial automation training institute is to select the preeminent alternative, the diverse group of experts find the suggested approach is highly useful technique for such type of selection.

Table 26
Validation of the proposed approach for Ex.2

	Proposed method		TOPSIS		SAW		GRA		COPRAS	
Alternatives	Performance index	Rank	Relative closeness	Rank	Composite score	Rank	Grey relational grade	Rank	Quantitative utility	Rank
G32F	3.4713	7	0.4377	6	2.3363	6	0.0680	5	97.5441	5
eNOVA OS	3.5455	6	0.4256	7	2.3297	7	0.0679	8	95.9629	8
SMART F43	4.0841	4	0.5340	3	2.3605	4	0.0682	3	97.8977	4
Ultima OF	4.4744	3	0.4637	5	2.3517	5	0.0680	6	98.2562	2
GE-32S	0.0000	11	0.3292	11	2.2558	11	0.0676	11	94.1025	9
GE-43F	4.9662	2	0.5133	4	2.3713	2	0.0682	4	98.0000	3
AU-3iA	0.7951	10	0.3663	10	2.2760	10	0.0677	10	88.7946	11
AL-400SA	5.7627	1	0.5789	1	2.3998	1	0.0684	1	100.0000	1
GA-43	2.7689	9	0.3952	9	2.3147	9	0.0679	7	90.3479	10
AP-4030A	3.8324	5	0.5620	2	2.3615	3	0.0683	2	96.8623	7
ZNC-30S	2.9239	8	0.4111	8	2.3197	8	0.0679	9	97.2395	6

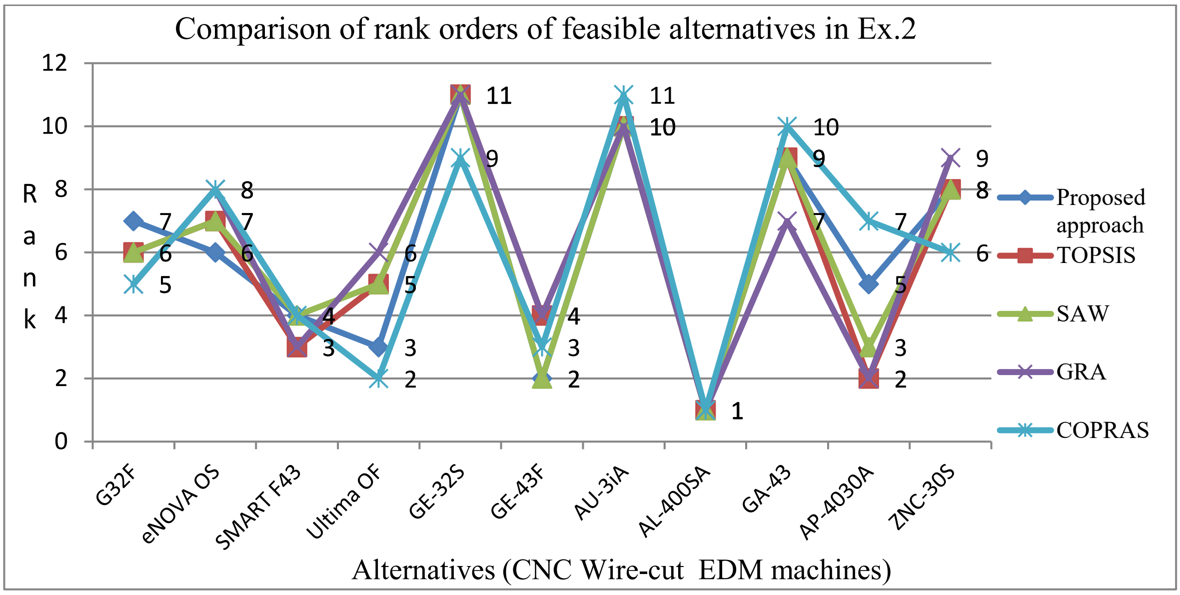

Fig. 4. Comparison of rank orders of feasible alternatives

4.2.1 Sensitivity analysis

As demonstrated in Ex. 1, the sensitivity analysis of the proposed approach in Ex. 2 is conducted and is represented in Fig.5. In this analysis, it is observed that rank reversals occur in no more than three instances across the decision-making attitudes in the proposed HGEDM approach. Table 25 shows that the top-ranked alternative AL-400SA has only one instance of rank reversal. The second-ranked alternative GE-43F experiences three instances of rank reversal. In the TOPSIS approach, it is found that rank reversal occurs in only two instances: for the top-ranked alternative AL-400SA and the second-ranked alternative GE-43F respectively. In SAW approach, rank reversals occur in three instances for alternative AL-400SA and three instances for alternative GE-43F. In the GRA approach, rank reversals occur in only two instances for the alternative

AL-400SA and in three instances for the GE-43F alternative. In COPRAS approach, the rank reversal trend is same as in SAW approach. The authors find that the trend in rank reversal is highly similar to those observed in Ex.1. The number of rank reversals in the proposed HGEDM approach closely matches those observed in well-established methods. The observed results of sensitivity analysis in Ex.1 & Ex.2 clearly indicate that the proposed approach is highly robust and stable.

4.2.2 Statistical analysis

From Table 27 it is observed that the SRC measures for the Suggested Method-TOPSIS, Suggested Method-SAW, Suggested Method-GRA, and Suggested Method-COPRAS are 0.91, 0.95, 0.84, and 0.89 respectively. These results indicate a strong positive linear relationship between the corresponding rank orders obtained using the proposed HGEDM approach and well-established methods as observed in Ex.1. For further verification of the effectiveness of the suggested method, the PCC and the SCC are computed and are presented in Table 27. These values are also very close to +1, indicating a high similarity between the proposed HGEDM approach and well-established methods. Ex.1 and Ex.2 establish that the proposed HGEDM approach is robust enough to be considered an effective decision-making tool.

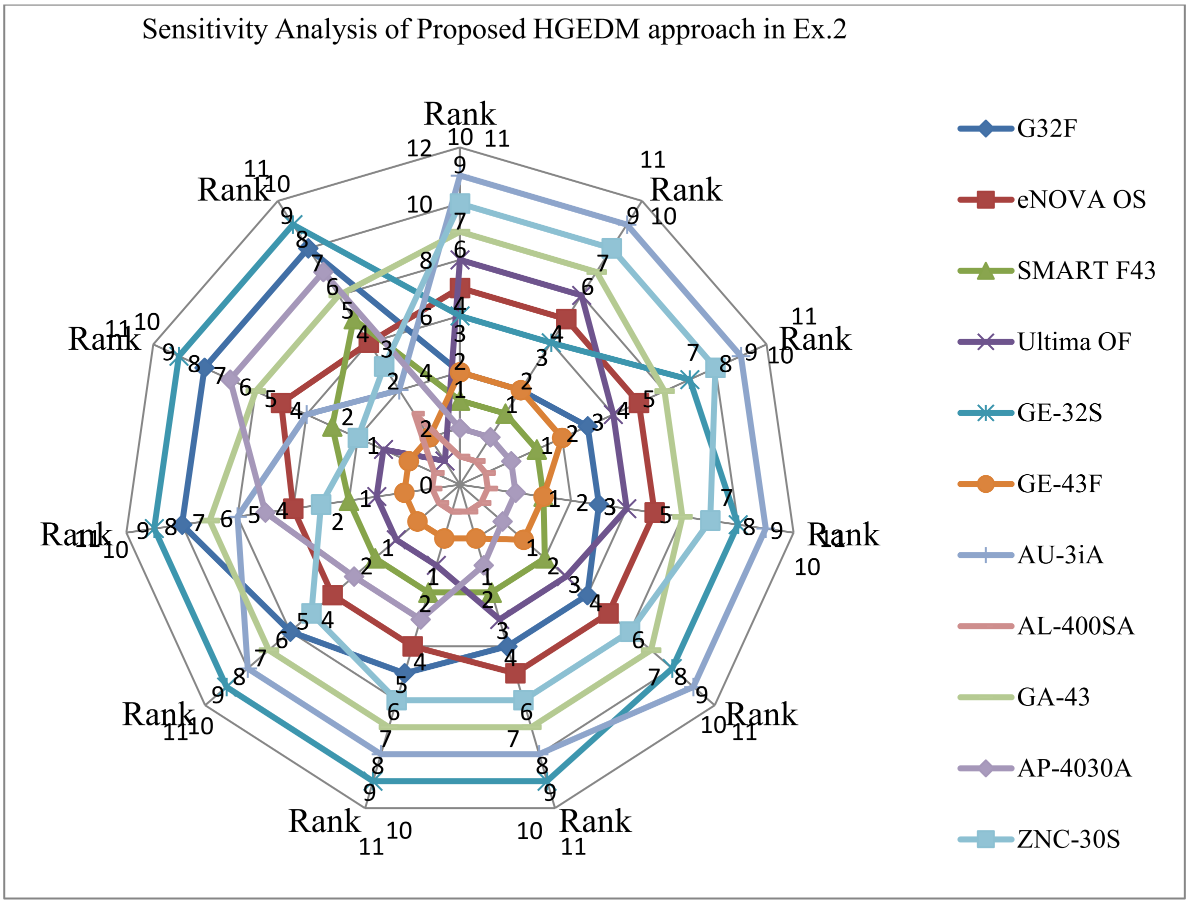

Fig. 5. Sensitivity analysis of the proposed approach (Ex.2)

4.3 Result analysis of Numerical Example 3

From Fig.6, it is observed that SBL GT-100 has the highest Performance Index (PI) measure (7.3074), making it the best alternative, while Art 350s+ has the lowest PI measure (0.0000), making it the worst among the chosen alternatives. Validation of the proposed approach is done similarly to Ex.1 and Ex.2 respectively. A comparison of the ranking orders of alternatives between existing approaches and the proposed approach is presented in Fig. 7 to show the closer position of the rank values across the different approaches. As observed in Ex. 1 and Ex. 2, the diverse group of experts also finds the proposed HGEDM approach in Ex. 3 is very suitable decision-making aid.

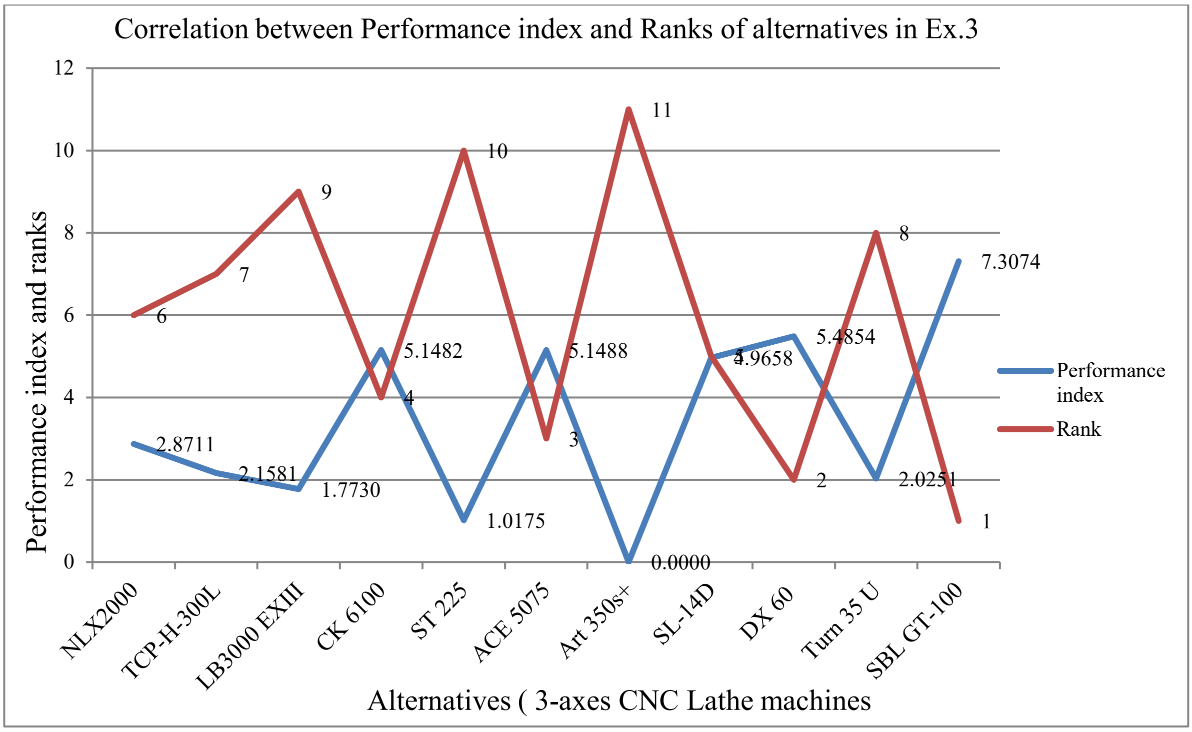

Fig. 6. Correlation between performance index and ranks of alternatives

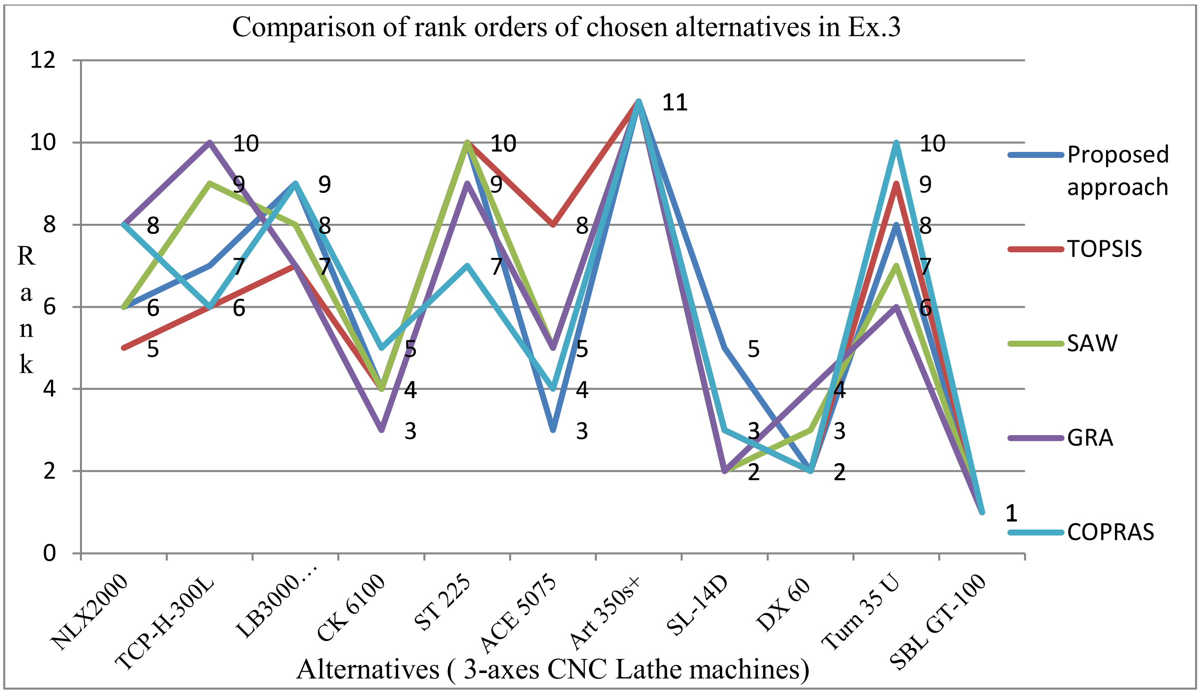

Fig. 7. Comparison of rank orders of alternatives

4.3.1 Sensitivity analysis

The sensitivity analysis for proposed HGEDM method in Ex. 3 is calculated similar to Ex.1 and Ex.2 and is represented in Fig.8. It shows that a slight tendency for rank positions of chosen alternatives to shift as α varies from 0.0 to 1.0. Table 25 shows that in the proposed approach, the top ranked alternative SBL GT-100 has three instances of rank reversal. The ranked 2 alternative DX 60 experiences also three instances of rank reversal. Similar to Ex. 1 and Ex. 2, the sensitivity analysis of the suggested HGEDM method in Ex.3 also shows a maximum of three rank reversals across alternatives. In TOPSIS approach, the rank reversals occur in three instances for alternative SBL GT-100 and two instances for alternative DX 60. In SAW approach, the rank reversals occur in two instances for alternative SBL GT-100 and three instances for alternative DX 60. In COPRAS approach, it is found that rank reversals occur in three instances: for the top-ranked alternative SBL GT-100 and the second-ranked alternative DX 60 respectively. Similar to the proposed approach, the GRA approach shows three instances of rank reversal for the top-ranked alternative SBL GT-100. The second-ranked alternative DX 60 also experiences three instances of rank reversal. The authors also find that the number of rank reversals in sensitivity analysis conducted across numerical examples vary from 1 to 3.Table 25 clearly specifies that the proposed approach is highly stable and can be recommended for judicious decision making in such type of selection fields.

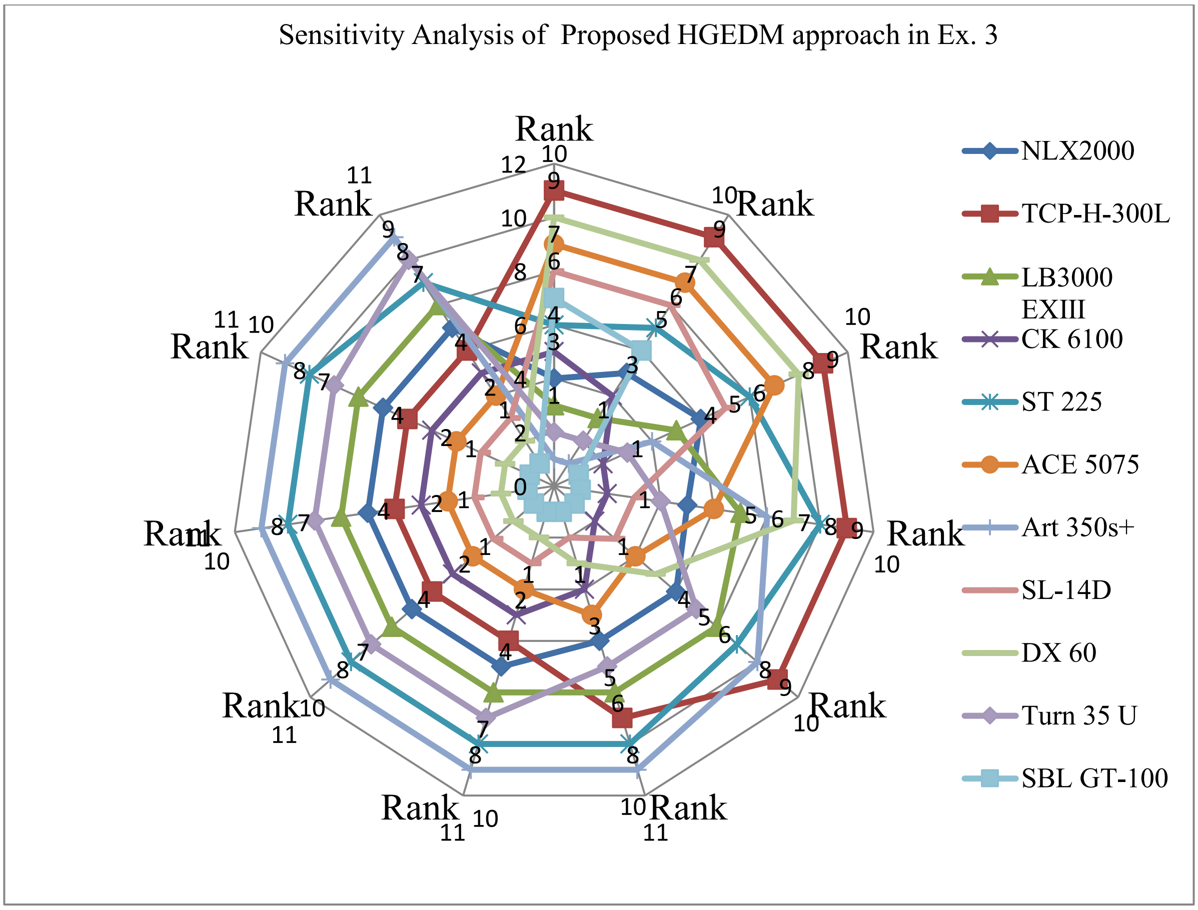

Fig. 8. Sensitivity analysis of the proposed approach (Ex.3)

4.3.2 Statistical analysis

From Table 27 it is observed that the values of the Spearman's correlation coefficients, Pearson correlation coefficient and the sample correlation coefficient in Ex. 3 have high similarity to those observed in Ex.1 and Ex.2. These values are also very close to +1, indicating a strong association between the proposed approach and well-established approaches. The illustrations of Ex.1, Ex.2, and Ex.3 establish that the proposed HGEDM approach is robust and adaptable, making it an effective decision-making tool.

5. Conclusions

The performance evaluation and selection of 3-axes CNC machines for an industrial organization is a complex task because improper evaluation can negatively impact manufacturing productivity and quality. The numerical examples and explanations in this research paper highlight several managerial characteristics of the proposed method, such as adaptability and informed decision-making. These aspects allow heterogeneous decision makers to share their opinions or provide ratings on the feasible alternatives, diverse criteria, and decision makers' competency in qualitative ways. These managerial traits also help to evaluate the potential strong points and drawbacks of a research problem. The significant contributions of this research article are abridged in the following ways:

- This research paper suggests a novel heterogeneous expert based decision methodology for evaluating performance of chosen alternatives and selecting the best option under vagueness.
- This approach involves a group of four diverse experts with varied academic qualifications, skills, domains, and potentially conflicting interests that results in a well-round decision to select unanimously the best alternative.
- The novel decision making framework considers the expert's impact factor which significantly contributes to evaluation and selection of alternatives.

- This approach takes into account few distinctive green attributes in the performance analysis of chosen alternatives, including energy utilization, toxic effect, dust pollution effect and local eco- friendly materials usage.
- The sensitivity analysis is carried out to establish the robustness and consistency of the proposed approach by showing a slight tendency for rank positions of the competitive alternatives to shift as the decision making attitude changes from 0.0 to 1.0.
- The comprehensive statistical analysis is carried out to validate the effectiveness of the suggested approach by demonstrating a more intense positive association among the proposed approach and well-established approaches in pairs.

Moreover, Table 27 shows that the Spearman's correlation coefficient, Pearson correlation coefficient, and Sample correlation coefficient in Ex.1, Ex.2 and Ex.3 are very close to +1, signifying a strong association between the proposed HGEDM approach and well-established methods. It establishes that the proposed HGEDM approach is robust and adaptable, making it an efficient decision-making approach. The comprehensive comparison of the statistical correlation coefficients derived from Ex.1, Ex. 2 and Ex.3 under the proposed methodology validates that the novel HGEDM method is a preeminent decision-making tool for evaluating and selecting such kind of capital equipment. While the suggested HGEDM approach offers valuable direction for selecting the best CNC machine, still it has some limitations including inadequate assessment criteria, the need for combination with other MCDM methods and evaluation of invariable decision.

Table 27

Statistical Analysis for suggested HGEDM approach Vs. well-existing approaches

Application	Correlation Coefficient	HGEDM Vs. TOPSIS	HGEDM Vs. SAW	HGEDM Vs. GRA	HGEDM Vs. COPRAS
Ex.1	SRC	0.98	0.94	0.81	0.85
	PCC	0.96	0.92	0.88	0.89
	SCC	0.96	0.92	0.88	0.89
Ex.2	SRC	0.91	0.95	0.84	0.89
	PCC	0.87	0.98	0.90	0.76
	SCC	0.87	0.98	0.90	0.76
Ex.3	SRC	0.84	0.91	0.82	0.89
	PCC	0.82	0.97	0.94	0.93
	SCC	0.82	0.98	0.94	0.94

Therefore, based on the above considerations, future research in this field could explore several directions:

- Developing a more robust version of the diverse expert group-based decision-making approach to achieve unanimous decision.
- Formulating a cognitive computing and data-driven learning based advanced MCDM model.
- Developing a Hybrid Expert-based approach can enhance robustness and efficacy of such kind of decision making tool.

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