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Multi-Criteria Decision Making (MCDM) in Non-Traditional Machining (NTM): A Review

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ABSTRACT

The manufacturing industry is increasingly adopting non-traditional machining (NTM) processes to meet the challenges posed by advanced engineering materials, intricate geometries, and tight dimensional tolerances. Despite their advantages, selecting and optimizing NTM processes is complex due to the presence of multiple, often conflicting, performance criteria such as material removal rate, surface integrity, tool wear, cost, and environmental impact, as well as numerous controllable process parameters. Multi-criteria decision-making (MCDM) techniques offer systematic and quantitative frameworks to evaluate, compare, and optimize such processes under competing objectives. This review provides a comprehensive examination of recent developments in the application of MCDM approaches to NTM, outlining the major evaluation criteria, widely used decision-making methods, and their applications across various industrial domains. Additionally, it highlights how MCDM contributes to process selection and parametric optimization when combined with mathematical modeling, statistical methods, or artificial intelligence tools. The paper concludes by identifying research gaps and suggesting promising future directions for sustainable and intelligent NTM process optimization.

KEYWORDS

Non-traditional machining, MCDM, process selection, parametric optimization, surface integrity.

1. INTRODUCTION

In modern manufacturing, traditional machining methods (such as turning, milling, and drilling) often struggle with difficult-to-machine materials (super-alloys, composites, and ceramics), complex features, micro-scale geometries, and increasingly stringent surface and dimensional requirements. This has led to the expanded adoption of non-traditional machining (NTM) processes — such as electrical discharge machining (EDM), waterjet machining (WJM/AWJM), laser machining, ultrasonic machining (USM), electrochemical machining (ECM), and hybrid methods[1], [2], [3], [4], [5].

While NTM offers advantages (capability to machine hard materials, produce complex shapes, minimal mechanical tool-workpiece contact), it also brings challenges: a large number of input parameters, conflicting output responses (e.g., maximise material removal rate (MRR) while minimising tool wear or surface roughness), and uncertain or non-linear process behaviour. Thus, the decision-making process for selecting a method and optimising parameters becomes multi-criteria in nature.[6], [7]

Non-Traditional Machining (NTM) encompasses a broad range of advanced manufacturing processes that differ fundamentally from conventional chip-removal techniques. As shown in Figure 1, NTM processes are classified based on the form of energy used for material removal, such as Electrical energy-based processes (e.g., EDM), which rely on spark erosion between an electrode and the workpiece. Electrochemical energy-based processes (e.g., ECM) remove material via anodic dissolution in an electrolyte. Mechanical energy-based processes (e.g., USM) use abrasive particles excited by ultrasonic vibrations to erode material. Thermal energy-based processes (e.g., laser cutting/drilling) utilize concentrated heat energy to melt or vaporize materials [8], [9], [10], [11]. Hydrodynamic energy-based processes (e.g., AWJM) employ high-velocity water or abrasive jets to cut materials. The classification highlights the diversity of energy mechanisms employed in NTM, enabling the machining of hard, brittle, or complex materials that are often difficult or impossible to machine by traditional methods. Each process offers unique advantages and challenges—such as surface integrity, precision, and cost—which makes multi-criteria decision making (MCDM) essential for process selection and parameter optimization[12], [13], [14], [15].

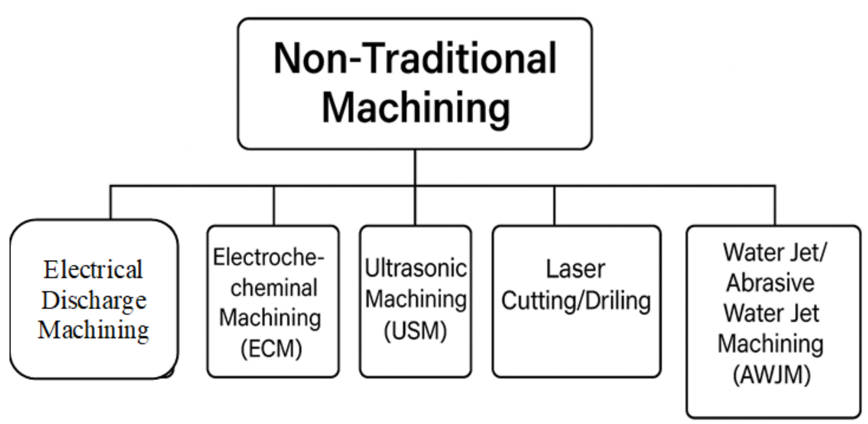

Figure 1: Classification of major Non-Traditional Machining (NTM) processes. The figure presents the principal NTM categories, including Electrical Discharge Machining (EDM), Electrochemical Machining (ECM), Ultrasonic Machining (USM), Laser Machining, and Water Jet/Abrasive Water Jet Machining (AWJM). These processes remove material using various non-mechanical energy sources such as electrical, chemical, thermal, or high-pressure kinetic energy.

MCDM techniques (such as AHP, TOPSIS, VIKOR, MOORA, GRA, COPRAS, PROMETHEE, etc.) provide tools for addressing these multi-criteria problems [16], [17], [18], [19], [20], [21]. In the context of NTM, such methods have been employed in both process selection (choosing among NTM alternatives) and parameter setting/optimization (selecting the optimal settings for a given process). This review aims to summarise the literature, highlight trends, identify gaps, and provide guidance for future work.

Figure 2 presents a conceptual framework that depicts how MCDM methods are used within the Non-Traditional Machining (NTM) domain to enhance process understanding and decision quality. Non-Traditional Machining (NTM) for this is the starting point of the framework, representing a diverse set of advanced machining processes (such as EDM, ECM, USM, AWJM, and laser machining). These processes are selected for their ability to machine hard or complex materials that conventional methods cannot handle. Process Selection for the first stage involves identifying the most suitable NTM process for a specific application based on multiple criteria—such as material type, desired surface finish, dimensional accuracy, cost, and environmental impact. MCDM assists in ranking and selecting the most appropriate machining method among several alternatives. Once the machining process is chosen, parametric optimization focuses on determining the best set of input parameters (e.g., current, pulse duration, jet pressure, feed rate) that balance multiple performance objectives, such as material removal rate (MRR), tool wear, and surface roughness. MCDM methods combine these criteria into a single composite performance index to identify optimal parameter settings. MCDM Techniques for this step integrate mathematical tools such as AHP, TOPSIS, GRA, VIKOR, or MOORA to analyse trade-offs among criteria. Weighting and ranking help convert multidimensional performance data into quantifiable, comparable results. Evaluation and Decision-Making for the final stage synthesizes the MCDM results to guide engineers in making informed, evidence-based decisions. The selected process or parameter set is validated experimentally or through simulation. This systematic approach enhances consistency, reduces subjectivity, and improves process efficiency.

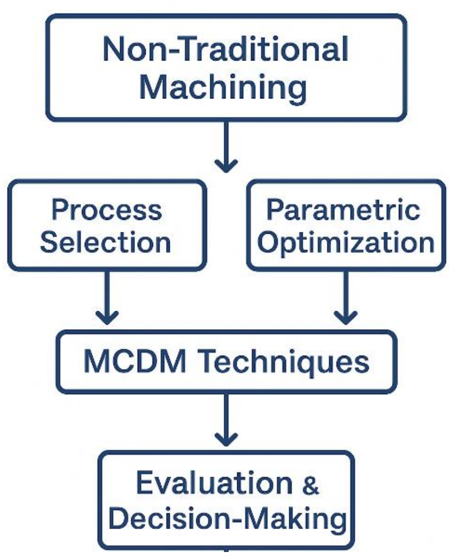

Figure 2: Framework for applying Multi-Criteria Decision-Making (MCDM) techniques in

Non-Traditional Machining (NTM). The schematic illustrates the integration of MCDM approaches in two primary stages—process selection and parametric optimization—leading to systematic evaluation and final decision-making.

2. FUNDAMENTALS OF MCDM AND NTM

2.1 OVERVIEW OF MCDM

Multi-criteria decision making (MCDM) refers to methods for evaluating, ranking, or choosing alternatives in the presence of multiple, often conflicting criteria. These criteria may be quantitative (e.g., MRR, tool wear rate) or qualitative (e.g., environmental impact, operator skill)[22], [23], [24], [25], [26], [27]. A typical MCDM workflow involves:

1. Defining the decision problem (alternatives, criteria)
2. Constructing the decision matrix (alternatives × criteria)
3. Assigning weights to criteria (often via AHP, CRITIC, entropy, expert judgement)
4. Normalising or scaling criterion values
5. Applying an MCDM algorithm (e.g., TOPSIS, VIKOR, MOORA) to rank alternatives or find optimum settings
6. Sensitivity or robustness analysis

Common methods include:

1. AHP (Analytic Hierarchy Process): pairwise comparisons to derive weights.
2. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution): identifies alternatives that are closest to the ideal and farthest from the worst possible outcome.
3. VIKOR: compromise solution considering group decision-making.
4. MOORA (Multi-Objective Optimization by Ratio Analysis): simple ratio-based ranking.
5. GRA (Grey Relational Analysis): handles incomplete information and multiple responses by converting them into a single grade of evaluation.
6. COPRAS, PROMETHEE, EDAS, MARCOS, CODAS: other outranking or utility-based methods.
   The choice of method depends on the nature of the criteria, the availability of data, the decision-maker's preference, and the computational complexity.

Table 1 provides a concise overview of commonly used MCDM methods in Non-Traditional Machining (NTM). Techniques like GRA and TOPSIS are widely applied for parametric optimization due to their simplicity and compatibility with experimental data. AHP is primarily used for determining criterion weights, while VIKOR and PROMETHEE are suitable for complex or group decision-making problems. Overall, MCDM methods facilitate the systematic evaluation of multiple conflicting criteria, thereby enhancing decision accuracy in the selection and optimization of processes.

Table 1: Overview of Common MCDM Techniques Used in Non-Traditional Machining

Method	Basic Principle	Advantages	Limitations	Typical Application in NTM
AHP (Analytic Hierarchy Process)[28], [29]	breaks complex decisions into a hierarchy; it uses pairwise comparisons to derive relative weights for criteria.	Easy to understand and implement; captures expert judgment effectively; supports group decision making.	Subjective; consistency of pairwise comparisons required; computationally intensive for many criteria.	Determining the weights of process criteria (e.g., MRR, Ra, cost) and selecting the optimal machining process.
TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)[30], [31]	ranks alternatives based on distance from the ideal (best) and negative-ideal (worst) solutions.	Intuitive and straightforward; considers both best and worst alternatives; quantitative results.	Sensitive to data normalization and weighting; assumes criteria are compensatory.	Parametric optimization in EDM, AWJM, and laser machining.
VIKOR[32], [33], [34], [35]	identifies a compromise solution closest to ideal, considering group utility and individual regret.	Handles conflicting criteria well; suitable for multi-stakeholder decisions.	Requires additional parameters (v-value); interpretation is less intuitive.	Process selection or ranking of NTM alternatives under conflicting objectives.

GRA (Grey Relational Analysis)[36], [37], [38]	converts multi-response data into a single grey relational grade to evaluate performance.	Handles incomplete or uncertain data; computationally simple; effective for Taguchi-based experiments.	Sensitive to reference sequence; limited interpretability for qualitative data.	Most used for multi-response optimization in EDM, ECM, and USM.
MOORA (Multi-Objective Optimization by Ratio Analysis)[39]	Normalizes data and ranks alternatives based on beneficial and non-beneficial criteria.	Straightforward; requires fewer computational steps; flexible.	Doesn't explicitly handle uncertainty or fuzzy data.	Multi-response optimization of laser machining, AWJM, and EDM.
COPRAS (Complex Proportional Assessment)[40], [41]	evaluates alternatives based on proportional significance of criteria.	Handles beneficial and non-beneficial criteria clearly; gives a utility degree.	Less popular; may yield inconsistent results under uncertainty.	Comparative assessment of process alternatives.
PROMETHEE[42], [43], [44]	Outranking method using preference functions for pairwise comparison.	Handles qualitative and quantitative data; flexible weighting.	Requires predefined preference functions; computationally complex.	Process selection under subjective or qualitative criteria.
EDAS (Evaluation Based on Distance from Average Solution)[45]	Ranks alternatives based on distance from average performance.	Objective and easy to calculate; avoids ideal/nadir assumptions.	Limited use in machining literature; not suited for small datasets.	Newer approach for ranking machining conditions.
MARCOS / CODAS[13], [21], [46], [47]	Recent utility-based MCDM methods using compromise or distance measures.	Offer balanced ranking stability; adaptable to hybrid models.	Limited adoption; methodological complexity.	Emerging research in hybrid MCDM frameworks.

2.2 OVERVIEW OF NON-TRADITIONAL MACHINING (NTM)

Non-traditional machining refers to processes that remove material without conventional cutting tool-workpiece mechanical contact (or where the contact is minimal/assisted)[48], [49], [50], [51]. Some major types:

1. Electrical Discharge Machining (EDM): spark erosion between the tool and workpiece in dielectric fluid.
2. Electrochemical Machining (ECM): material removal via electrochemical dissolution.
3. Ultrasonic Machining (USM): abrasive particles driven by ultrasonic vibration.
4. Laser Cutting/Drilling: thermal ablation via focused laser beam.
5. Water Jet / Abrasive Water Jet Machining (AWJM): high-velocity water or abrasive slurry jet.
6. Hybrid Methods: e.g., ultrasonic-assisted EDM, laser-assisted machining, etc.

Table 2 presents the Non-Traditional Machining (NTM) processes, which utilize various energy forms—electrical, chemical, thermal, or mechanical—to remove material without direct cutting action. Each process, as outlined in the table, offers unique benefits suited to specific materials and applications. EDM and ECM are ideal for conductive materials, while USM, LBM, and AWJM are effective for handling hard or brittle materials. Selecting the most appropriate NTM process depends on multiple performance and cost criteria, often supported by MCDM techniques for rational decision-making.

Table 2: Overview of Non-Traditional Machining (NTM) Processes

Process	Energy Source / Principle	Key Process Parameters	Major Advantages	Limitations	Typical Applications
Electrical Discharge Machining (EDM)[52]	Electrical energy—spark erosion between tool and workpiece in dielectric fluid.	Pulse current, pulse-on/off time, voltage, duty factor, tool material, flushing pressure.	Can machine rigid and conductive materials; complex shapes are achievable; no	Slow material removal rate, tool wear, and surface micro-cracks.	Tool & die making, aerospace alloys, micro-hole drilling.

			mechanical contact.		
Electrochemical Machining (ECM)[53]	Electrochemical dissolution using DC and electrolyte.	Current density, electrolyte flow rate, voltage, and inter-electrode gap.	No tool wear; excellent surface finish; stress-free machining.	High setup cost; conductive materials only; electrolyte disposal issues.	Precision components, turbine blades, medical implants.
Ultrasonic Machining (USM)[54]	Mechanical vibration of the tool with abrasive slurry impacts the material surface.	Frequency, amplitude, abrasive size, feed rate, and slurry concentration.	Suitable for hard and brittle materials; minimal heat generation.	Low MRR; tool wear; limited to shallow cavities.	Glass, ceramics, carbides, and semiconductor machining.
Laser Beam Machining (LBM)[55], [56]	Thermal energy from a focused laser beam melts or vaporizes material.	Laser power, pulse duration, focal position, and scan speed.	High precision, no tool wear, and micro-feature capability.	Heat-affected zone; expensive setup; limited by material reflectivity.	Micro-drilling, engraving, and cutting of metals and composites.
Abrasive Water Jet Machining (AWJM)[57], [58]	High-velocity water jet with abrasive particles erodes material.	Jet pressure, traverse speed, abrasive flow rate, and stand-off distance.	Can cut any material; no thermal damage; eco-friendly.	Noisy; kerf taper; limited precision for fine features.	Cutting composites, ceramics, metals, and stone.
Plasma Arc Machining (PAM)[59]	Ionized gas (plasma) melts and removes material by high-velocity jet.	Arc current, gas flow rate, nozzle diameter, and stand-off distance.	High cutting speed; good for thick sections.	Large heat-affected zone; rough surface finish.	Cutting thick metal plates and structural components.
Electron Beam Machining (EBM)[60], [61]	Focused electron beam melts and vaporizes	Beam current, accelerating voltage, and	Very high precision; suitable for	Requires a vacuum chamber; limited to	Micro-hole drilling, aerospace,

	material in a vacuum.	focus position.	micro-holes.	conductive materials.	and electronic components.

NTM processes are widely used for hard-to-cut materials (super alloys, ceramics, composites), micro features, complex shapes, and tight tolerances, as well as applications in aerospace, medical, energy, and tooling industries. However, they bring many process variables (e.g., pulse on/off time, current, voltage for EDM; jet pressure, stand-off distance for AWJM; laser power, scan speed for laser) and multiple responses (MRR, surface roughness, kerf width/taper, recast layer, tool wear, heat-affected zone, cost, environmental effect). The presence of multiple conflicting objectives makes MCDM highly relevant.

3. APPLICATION OF MCDM IN NTM – PROCESS SELECTION

Selecting the most appropriate NTM process for a given workpiece/material/feature is a classical MCDM problem: the alternatives are different NTM processes, and the criteria cover technical, economic, environmental, and operational aspects. For example, Multi-criteria decision making has been applied in process selection, in the paper by Miloš Madić et al. [62] titled "Selection of non-conventional machining processes using the OCRA method", the authors modelled the process selection problem as MCDM and used the OCRA method to evaluate three case studies. Their results aligned well with previous studies using different MCDM methods. Assisted in the development of another work that created an intelligent decision model for NTM parameter/response guidance [19], [63], [64], [65], [66], [67], [68], [69].

Key criteria often used in process selection include:

1. Technical: material compatibility, achievable geometry/feature size, dimensional accuracy, surface roughness, material removal rate
2. Economic: cost per part, tool cost, cycle time, setup cost
3. Operational: machine availability, flexibility, required operator skill
4. Environmental/sustainability: power consumption, consumables, waste/debris handling
5. Safety and reliability

Typical workflow: Define alternatives (e.g., EDM, AWJM, USM), define criteria, assign weights (via AHP, CRITIC), score each alternative, apply MCDM (TOPSIS, MOORA, OCRA), rank alternatives. **Observations and trends**:

1. Process-selection papers often rely heavily on expert judgement for weights and scoring (thereby introducing subjectivity).
2. Many papers use AHP or hybrid AHP-TOPSIS approaches.
3. The number of criteria is sometimes limited to keep complexity manageable.
4. There is less work on integrating uncertainties (fuzzy MCDM, intuitionistic fuzzy sets) in NTM process selection compared to other domains.

4. APPLICATION OF MCDM IN NTM – PARAMETRIC OPTIMISATION

Beyond selecting the process, a significant application of MCDM in NTM is *parametric optimisation* — choosing the best settings of input parameters for a given NTM process such that multiple performance responses are jointly optimised (e.g., maximising MRR, minimising surface roughness, minimising tool wear).

4.1 Literature trends

A review by Devendra Pendokhare et al. [63]2022) used MCDM techniques for this purpose. Frontiers. Their findings include:

1. The most common experimental plan: Taguchi L_9 orthogonal array[63].
2. Most-machined materials: medium and high carbon steels ~34.3%, then Ti alloys 14.6%, Al alloys 13.9%, Inconel 10.2% etc[63].
3. Input parameters: peak current (Ip) ~97.8%, Ton (pulse-on time) ~94.2%, voltage.[63]
4. Responses: MRR (~92.7% of papers), tool wear rate (~74.5%), surface roughness (~73.0%)[63].
5. MCDM methods: GRA (Grey Relational Analysis) is the most used (~52.6%), then TOPSIS (~9%), MOORA (~3.65%), VIKOR (~3.65%), etc[63].
6. A broader review by Kanak Kalita et al. (2022) on the parametric optimisation of non-traditional machining (not only EDM) using MCDM provides a dataset. It identifies GRA and TOPSIS as the dominant tools [70].
7. **4.2 Typical methodology**

In parametric optimisation, the process is often structured as follows:

1. Conduct designed experiments (Taguchi, Box-Behnken, RSM) varying input parameters at specified levels.
2. Measure responses (MRR, surface roughness, tool wear rate, kerf width, recast layer, energy consumption, etc.).
3. Form a decision matrix where each trial is an alternative, and responses are criteria (some to be maximised, some minimised).
4. Assign weights to each criterion (equal or via weighting methods like AHP, CRITIC).
5. Convert responses to benefit/cost form (normalisation).
6. Apply an MCDM method (GRA, TOPSIS, MOORA) to compute a composite performance index for each experiment/trial.
7. Identify the trial with the highest performance index as the optimal parameter setting.
8. Validate via confirmation experiments.

4.3 Strengths and limitations

- MCDM enables the consideration of multiple conflicting objectives in a systematic and quantifiable manner.
- It simplifies decision-making for practitioners by converting multiple responses into a single performance index.
- It can reduce experimentation cost by identifying promising settings from existing trials rather than brute-force optimisation.

Limitations:

- Many studies assign equal weights to criteria without justification, which may not reflect actual stakeholder preferences. Pendokhare et al. point this out[71].
- The decision matrix is often based purely on experimental trials done for individual purposes; the spectrum of alternatives may be limited.
- Often, uncertainty, variability, and robustness of the optimum are not analysed. Few studies integrate fuzzy logic or uncertainty modelling.
- Most studies focus on a single process (e.g., EDM) rather than cross-process comparison.
- Many studies rely on simple MCDM, with relatively little work on hybrid MCDM and the integration of metaheuristics or machine learning.

4.4 Example applications

- In the study by M. Madić et al. [62]the OCRA method was used for process selection of NTM.

- In the work by S. Chakraborty and Vidyapati Kumar [70], an intelligent decision model was developed for NTM processes, guiding parameter settings for target responses.

Process selection in Non-Traditional Machining (NTM) involves evaluating several machining alternatives under multiple, often conflicting criteria. As shown in Figure 3, MCDM techniques offer a structured approach to balancing key factors, including workpiece material compatibility, desired surface finish, dimensional accuracy, and manufacturing cost. In this framework, each criterion is assigned a weight based on its relative importance, and MCDM methods—such as AHP, TOPSIS, or VIKOR—are applied to rank available processes. For instance, EDM may be preferred for conductive and hard materials, AWJM for composites requiring minimal thermal damage, and USM for brittle ceramics. This systematic evaluation enables engineers to select the optimal process that meets both performance and cost objectives, thereby improving decision transparency and manufacturing efficiency.

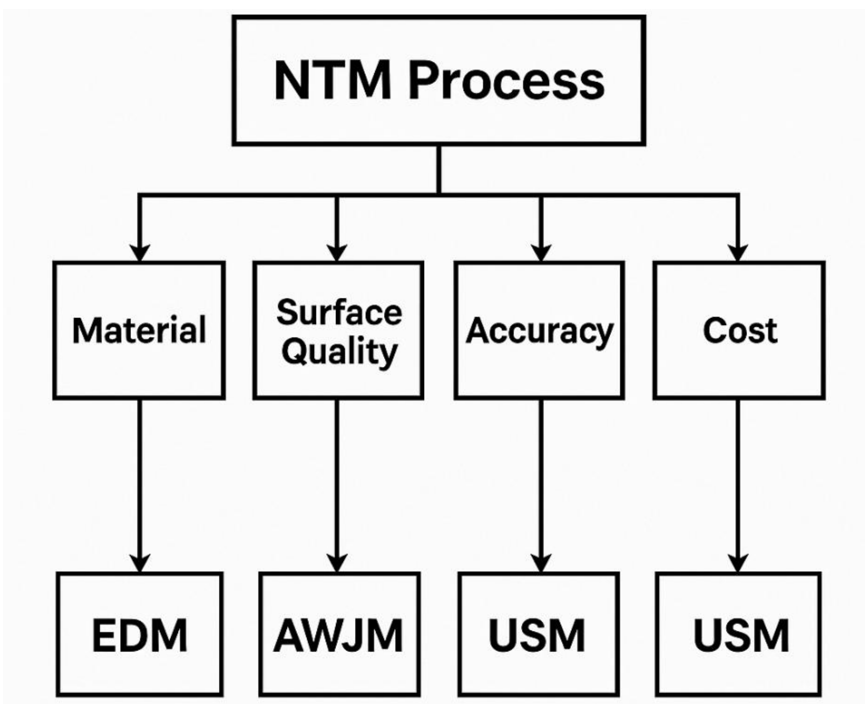

Figure 3: Application of Multi-Criteria Decision-Making (MCDM) in Non-Traditional Machining (NTM) for process selection. The diagram illustrates how multiple decision criteria—such as material type, surface quality, dimensional accuracy, and cost—are evaluated using

MCDM methods to identify the most suitable NTM process (e.g., EDM, AWJM, USM).

In a comparative study of the turning of Ti6Al4V alloy (conventional, ultrasonic-assisted, and hot ultrasonic-assisted), the authors used the reference ideal MCDM method to rank alternatives, considering surface roughness, stable cutting depths, and tool temperature. They recommended higher cutting speeds, lower tool overhang lengths, and ultrasonic-assisted turning.

5. KEY CRITERIA AND PARAMETERS IN NTM MCDM STUDIES

To apply MCDM in NTM, one must define the criteria (responses) and identify key process parameters. Below is a summary.

5.1 Common parameters (inputs)

Depending on the specific NTM process, standard input parameters include:

1. For EDM: pulse-on time (Ton), pulse-off time (Toff), peak current (Ip), voltage (Vg), duty factor, dielectric flushing, and tool material. (See Pendokhare et al.) [71], [72].
2. For USM: abrasive size, vibration amplitude, feed rate, ultrasonic power, and tool material.
3. For AWJM: jet pressure, stand-off distance, traverse speed, abrasive flow rate, nozzle diameter.
4. For laser machining, the following parameters are essential: laser power, pulse energy, scan speed, focal position, and assist gas flow.
5. For ECM: electrolyte concentration, current density, feed rate, gap voltage, and tool feed.

5.2 Common performance responses (criteria)

Frequent output criteria used in MCDM in NTM include:

1. Material Removal Rate (MRR) – typically to be maximised.
2. Tool Wear Rate (TWR) or Electrode Wear – to be minimised.
3. Surface Roughness (Ra, Rq) or surface integrity (recap layer, microhardness) – to be minimised / quality improved.
4. Kerf width or kerf taper (in AWJM / laser) – to be minimised.
5. Dimensional accuracy or form error – to be minimised.
6. Energy consumption and cost per part are to be minimized.

7. Environmental/operational criteria: waste/debris generation, ease of setup, flexibility – to be minimised or maximised depending on context

5.3 Weighting and criteria-trade-offs

Because responses often conflict (for example, increasing MRR may worsen surface roughness or increase tool wear), MCDM must trade off these criteria. The assignment of weights is critical. Methods include:

1. Subjective methods: AHP, expert judgement
2. Objective methods: CRITIC (Contrast intensity and conflict), entropy method, PCA
3. Hybrid methods: combining subjective and objective weights

Finally, Figure 4 highlights the major decision factors influencing MCDM applications in NTM. The performance criteria (e.g., MRR, surface roughness, tool wear) evaluate machining effectiveness, while cost criteria (machining cost, tool and setup expenses) reflect economic considerations. Quality criteria focus on dimensional accuracy and surface integrity, crucial for precision manufacturing. The weights of the requirements define the relative importance of each factor, determined using methods such as AHP or entropy. Finally, process parameters—such as voltage, pulse duration, jet pressure, and abrasive flow rate—directly affect machining outcomes. Together, these elements form the foundation for applying MCDM techniques to evaluate, optimize systematically, and rank machining alternatives.

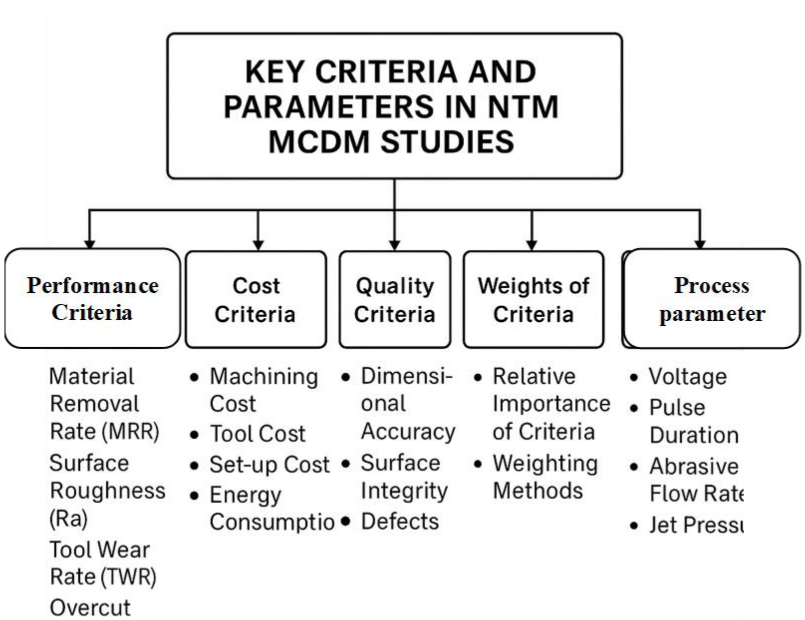

Figure 4: Key criteria and parameters considered in Multi-Criteria Decision-Making (MCDM)

studies for Non-Traditional Machining (NTM). The diagram categorizes essential factors, including performance, cost, quality, weighting, and process parameters, that influence optimization and selection decisions in NTM research.

Many studies assign equal weights, which may oversimplify the reality. As Pendokhare et al. note: "in most of the MCDM methods, equal importance (weight) has usually been assigned to the considered responses to avoid mathematical complexity," but they also recommend objective weighting to derive more pragmatic solutions.

6. COMPARATIVE OVERVIEW OF MCDM METHODS IN NTM CONTEXT

This section compares the strengths, weaknesses, and suitability of various MCDM methods as used in NTM literature. From the review by Pendokhare et al., GRA has been most frequently used in EDM parametric optimisation (~52.6% of papers), followed by TOPSIS (~9%) and MOORA/VIKOR (~3.6%)[72].

Table 3 summarizes the commonly used MCDM methods in Non-Traditional Machining (NTM), comparing their strengths, weaknesses, and suitability. AHP is preferred for determining weights based on expert judgment, while TOPSIS and GRA are the most frequently applied for parametric optimization due to their simplicity and ability to handle multiple responses. VIKOR is useful for compromise-based decisions, and MOORA is favored for quick computations with many alternatives. Newer methods, such as COPRAS, EDAS, and MARCOS, show potential but remain less explored in machining research.

Table 3 Comparative Characteristics of Edge, Cloud, and Hybrid Architectures for Real-Time MCDM-Based Quality Control

Method	Strengths	Weaknesses	Suitability in NTM
AHP[73]	Intuitive, widely used for weighting, suitable for hierarchical decision structure	Time-consuming pairwise comparisons, subjective bias	Good when criteria weights need to be elicited from experts (e.g., process-selection)
TOPSIS[74]	Simple calculation, conceptually precise (distance to ideal)	Sensitive to normalization/scaling, assumes criteria are compensatory	Widely used in parametric optimisation in NTM

VIKOR[32]	focuses on a compromise solution, group decision support	Requires specification of a "v" parameter, which is less intuitive	Suitable when decision makers need to compromise among the criteria
MOORA	Simple ratio-based method, with less computational overhead	Doesn't handle non-compensatory criteria well	Suitable for parametric optimisation with many alternatives
GRA	Handles incomplete information, suitable for multiple responses	Requires reference sequence selection, less intuitive ranking	Very popular in NTM parametric optimisation (per reviews)
COPRAS / EDAS / MARCOS / CODAS	More recent outranking/utility methods	Less widely known in the machining field, more complex	Potentially useful but less common in current NTM literature

The bar chart in Figure 5 shows that GRA is the most frequently applied MCDM method in NTM studies due to its simplicity and effectiveness in handling multiple responses. TOPSIS and MOORA are also popular for parametric optimization, offering transparent and interpretable results. In contrast, advanced methods such as VIKOR, COPRAS, and EDAS are less common but are gaining attention for their ability to manage complex decision-making scenarios.

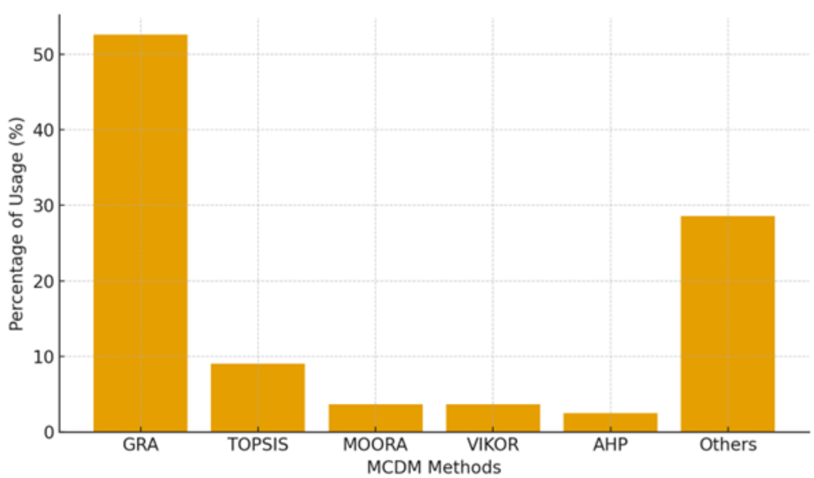

Figure 5: Comparative overview of MCDM methods used in Non-Traditional Machining (NTM) research. The chart illustrates that Grey Relational Analysis (GRA) dominates with over 50% usage, followed by TOPSIS, MOORA, and VIKOR. At the same time, AHP and other emerging methods (COPRAS, EDAS, MARCOS, etc.) have limited adoption.

7. Research Gaps and Future Directions

Based on the surveyed literature, several research gaps and opportunities can be identified.

7.1 Broader process coverage

Most MCDM work in NTM targets EDM (electrical discharge machining). There is less MCDM-based work on other NTM processes (AWJM, laser machining, ECM, hybrid methods). Expanding to a broader spectrum of NTM will increase applicability.

7.2 Integration with uncertainty modelling and fuzzy/intuitionistic sets

Very few studies incorporate uncertainty (measurement error, variability in process responses), fuzzy sets, intuitionistic fuzzy MCDM, or robust decision-making frameworks. As decision-making in manufacturing often involves uncertainty, this is a promising area for exploration.

7.3 Hybridisation of MCDM with machine-learning / metaheuristics

While metaheuristic optimisation (GA, PSO) and machine learning modelling (ANN, ANFIS) have been used in machining optimisation, their integration with MCDM for decision support is less developed. Combining predictive modelling with MCDM could yield more intelligent decision frameworks.

7.4 Objective weighting and sensitivity analysis

Many existing studies default to equal weights for criteria. There is a need for objective weighting (CRITIC, entropy) and sensitivity analysis of weights to evaluate the robustness of ranking results.

7.5 Sustainability and environmental criteria

As manufacturing becomes greener, criteria related to energy consumption, tool-coolant recycling, waste generation, and life-cycle cost should be integrated into MCDM for NTM. Few studies have considered such sustainability metrics so far.

7.6 Real-time decision support systems

Most studies are offline and academic. Developing real-time decision support frameworks (dashboard, expert system) for process engineers that embed MCDM logic could enhance practical adoption. For example, the intelligent decision model in Chakraborty & Kumar [70] is a step in this direction.

7.7 Multi-process or hybrid process decision making

In many industries, selecting among or combining multiple machining technologies (traditional, non-traditional, or hybrid) is relevant. MCDM frameworks that consider hybrid process combinations and transitions would be valuable.

Figure 6 outlines the significant research gaps and emerging directions in MCDM applications within NTM. Future studies should focus on expanding MCDM applications to a broader range of machining processes beyond EDM and AWJM. Developing hybrid and fuzzy MCDM models will improve decision-making accuracy under uncertainty. Incorporating sustainability and green manufacturing criteria can enhance environmental and economic performance. Ultimately, the integration with Industry 4.0—encompassing intelligent data analytics, AI, and digital twins—will facilitate real-time, adaptive decision-making in advanced manufacturing environments.

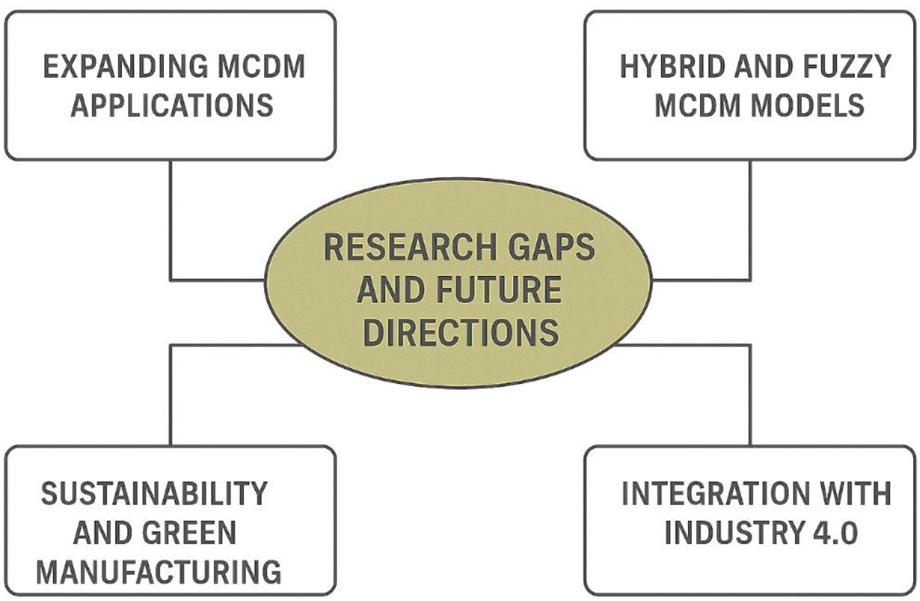

Figure 6: Research gaps and future directions in applying Multi-Criteria Decision-Making (MCDM) to Non-Traditional Machining (NTM). The figure highlights key focus areas for future work, including expanding applications, developing hybrid and fuzzy MCDM models, integrating sustainability, and aligning with Industry 4.0 technologies.

8. Practical Guidelines for Implementing MCDM in NTM

For practitioners and researchers looking to deploy MCDM in NTM contexts, here are some recommended guidelines derived from the literature and experience:

1. Define problem clearly: Decide whether you are selecting a process (alternatives = processes) or optimizing parameters (alternatives = experimental runs or parameter settings).
2. Select appropriate criteria: Identify key technical, economic, operational, and sustainability requirements. Distinguish beneficial (to maximise) vs non-beneficial (to minimise) responses.
3. Collect reliable data: For parametric optimisation, use well-designed experiments (Taguchi, RSM) or real industrial data. Ensure data quality and repeatability.
4. Weight criteria meaningfully: Use AHP or expert survey if you need subjective weights; use objective methods (CRITIC, entropy) to justify weights or validate them. Conduct sensitivity analysis.
5. Choose the MCDM method suited to the context. For many machining optimisation problems, GRA or TOPSIS may be sufficient. For process selection where group decision makers are involved, VIKOR or PROMETHEE might be more appropriate.
6. Normalise and process data carefully: Ensure proper scaling of responses, manage units, and convert all criteria into a benefit/cost form before applying ranking.
7. Validate results: After ranking or obtaining optimal parameter settings, conduct confirmation experiments or field trials to verify the findings.
8. Perform sensitivity/robustness study: Check how rankings or optimums change with changes in weights or measurement uncertainty.
9. Consider decision support tools: If the decision-making framework will be used by engineers on the floor, consider building a GUI/Expert system (see Chakraborty & Kumar, [70]).
10. Document assumptions and limitations: Clearly state assumptions (weights, criteria independence, data validity) and constraints (scope of alternatives, uncertainty unmodelled) in your study.

Figure 7 presents a structured workflow for the practical application of Multi-Criteria Decision-Making (MCDM) techniques in the Non-Traditional Machining (NTM) domain. This framework ensures a logical, transparent, and reproducible process for making complex machining decisions that involve multiple performance and cost-related criteria.

The first step, "Define Decision Criteria and Objectives," is fundamental to any MCDM-based study. Researchers and engineers must clearly identify both the objectives (e.g., maximizing productivity, minimizing tool wear, achieving better surface finish) and the decision criteria (such as MRR, surface roughness, tool wear rate, energy consumption, and cost). Defining clear, measurable criteria ensures that the decision problem is structured properly and aligns with the goals of the machining operation.

The second step, "Choose Appropriate MCDM Technique," involves selecting a method that is suited to the nature of the problem and the data. For example, TOPSIS or GRA may be chosen for straightforward parametric optimization due to their simplicity and quantitative clarity. In contrast, AHP is ideal when subjective judgment or hierarchical weighting is required. In comparison, VIKOR or PROMETHEE might be preferred in multi-decision-maker or compromise scenarios. The selection should consider the data type, the number of alternatives, and the computational effort.

Next, "Perform Normalization and Weighting" standardizes the criteria so they can be compared on a standard scale. Since machining responses often have different units (e.g., µm for surface roughness, g/min for MRR, seconds for cycle time), normalization ensures fair comparison. Weighting assigns relative importance to each criterion—either subjectively (via AHP or expert judgment) or objectively (using entropy or CRITIC methods). Accurate weighting is critical as it directly affects ranking outcomes.

The final step, "Conduct Analysis and Sensitivity Assessment," integrates all the normalized and weighted data to produce a final ranking or performance score for each alternative. This helps identify the optimal process or parameter setting. A sensitivity analysis is then performed to examine how changes in weights or input data affect the results, ensuring that the final decision is robust and not overly dependent on specific assumptions. Such validation enhances the credibility and industrial applicability of the findings.

Overall, these practical guidelines provide a comprehensive roadmap for researchers and practitioners to effectively implement MCDM in NTM studies. By following this structured approach, one can ensure that the decision-making process is systematic, transparent, and data-driven, ultimately leading to better optimization and process selection in advanced machining environments.

9. CONCLUSION

The application of multi-criteria decision-making (MCDM) techniques in non-traditional machining (NTM) has grown significantly, especially in the area of parametric optimization and, to a lesser extent, process selection. MCDM methods help reduce complexity, synthesise multiple conflicting objectives, and provide structured decision support for process engineers. Key trends include the dominance of GRA and TOPSIS in parametric optimization, as well as AHP-based weighting in process selection studies. Yet, essential gaps remain — including broader process coverage, better handling of uncertainty and sustainability criteria, integration with machine-learning/metaheuristic methods, and development of real-time decision support. By addressing these gaps, future research and industrial practice can further enhance the adoption and impact of MCDM in NTM.

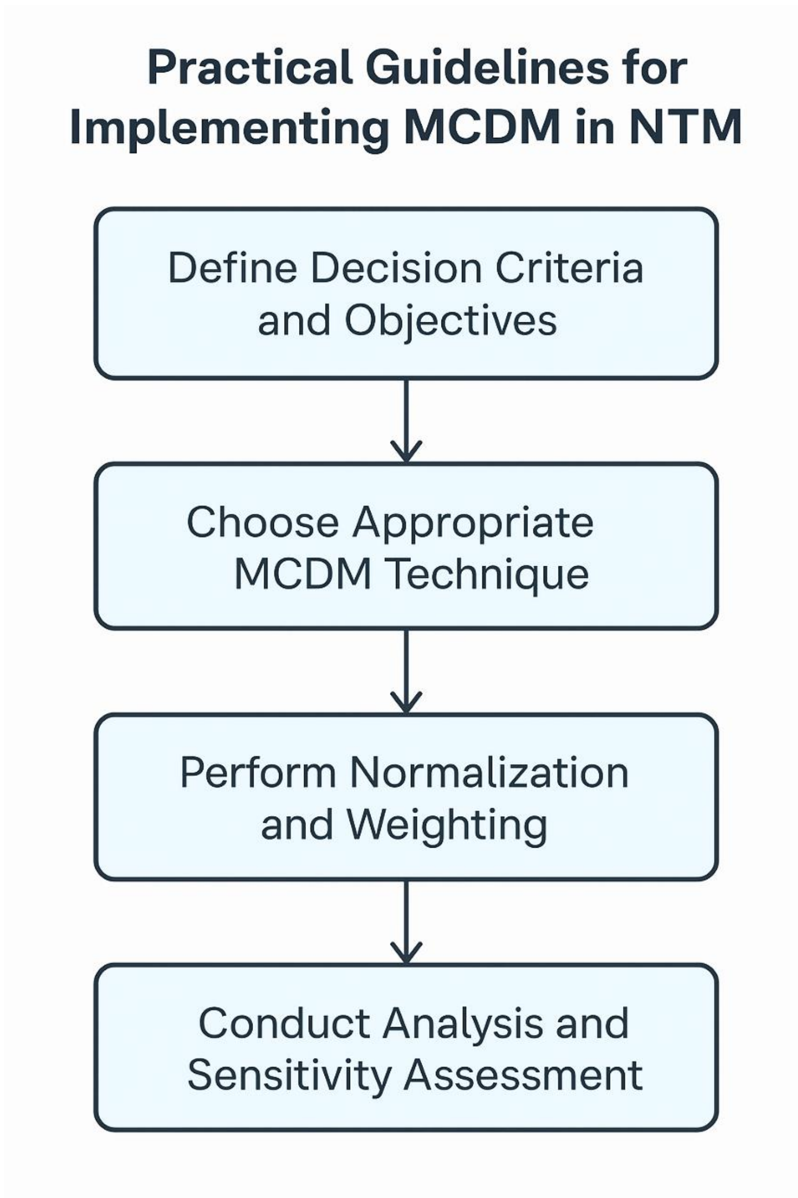

Figure 7: Practical guidelines for implementing Multi-Criteria Decision-Making (MCDM) in Non-Traditional Machining (NTM). The flowchart summarizes the key steps involved—from defining decision criteria to conducting normalization, weighting, and sensitivity analysis—to ensure systematic and reliable decision-making.

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