Application of M-polar Fuzzy Set Algorithm for Nontraditional Machining Process Selection

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Abstract Developed machining processes for hard materials are known as non-traditional machining (NTM) processes. The selection of the best NTM process in the manufacturing industry is a significant problem. In this paper, literature related to decision expert systems and data collected for NTM processes analyzed and an m-polar fuzzy set based selection of NTM processes methodology is developed. A conceptual design of the m-polar fuzzy set system is explained and implemented. Two problems are solved with the method. Problem solved by m-polar fuzzy set algebra is considering subgroups of parameters. The m-polar fuzzy set algorithm methodology is explained step by step. It gives nearly the same results as obtained in previous literature work for obtaining through cavities in metals and non-metals. It's observed m-polar fuzzy set can be used in the selection of the NTM process.

Keywords m-polar · Fuzzy set · Expert system · NTMPs

1 Introduction

In modern industry manufacturing practices, it is a daily job to machine materials with mechanical properties like toughness, hardness and higher strength. In sectors like automobile, tool and die making utilizes materials such as ceramics, titanium, composites and refractory alloys, which are difficult for creating accurate and complicated shapes. Complex shapes machining on tougher materials cannot be done with conventional machining processes identified for material removal in the form of a chip. Due to such limitations of traditional machining processes, change in manufacturing has been taking place since 1940. New tools and new forms of energy

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were utilized in the latest manufacturing era to achieve more sophisticated designs on complex machine materials [13].

NTM Processes have vague data. Every NTM Process requires the specific value of parameters as an optimum value. Tables 1, 2 and 3 explain NTM process data cognitively. Data describes the extent of process operations compared to its maximum limits. In Table 1 [10], various shape applications of NTM Processes are explained in a cognitive way, where the scale of various operations performed by NTM processes are divided into "Good" and "Fair", then with the eleven-point scale converted into quantitative values as per Table 5.

In Table 2 material application for metals, alloys and non-metals explained with respect to various NTM processes is explained in quantitative form with the help of eleven-point scale.

In Table 3 economics of different NTM processes are explained considering various costs like capital cost, tooling cost, power consumption cost, material removal rate efficiency, and tool wear cost.

In Table 4 various methods used for NTM process selection are discussed with various aspects like flexibility, computational time, programming complexity, decision-makers involvement and type of data used for the analysis.

Material applications of metals and alloys are explained by [6], where he relates various NTM Processes applications with metals and non-metals. The scale used to describe the applications is "Poor", "Fair" and "Good". Economics of NTM Processes is the essential factor during selection for suitable application. Yurdakul and Cogun [15] divides economics of NTM processes in Power consumption cost, Material removal rate efficiency, Capital cost, Tool wear and Tooling cost with scale "Very low", "low", "Medium" and "High". Table 5 shows eleven-point scale which can be used to convert linguistic variables into quantities.

Various methods are utilized in NTM processes selection. These methods have different Operational approaches, different performances and different outputs. Table 4 explained by Boral S. Genetic algorithm is having medium flexibility with numerical work. On the other hand, an artificial Neural Network is highly flexible with Numerical data output with high computational time. Simulated annealing with medium flexibility and medium computational time with numerical results. The expert system method is widely used due to its operational approach with medium flexibility and medium computational time with numerical and textual outputs considered in NTM process selection. Further, the Case-Based Research (CBR) method depends on similarity and takes low computational time with numerical and textual outcomes considered practical by several researchers.

The selection of NTM processes is a multi-criteria decision-making problem. Researchers are finding hybrid methods to get the exact selection process. Table 6 shows that the Authors are working on getting results from various MCDM techniques. They are achieving it quite often while implementing NTM processes. It is observed that most of the methods are not considering the uncertainty involved in the problem. Also, it comes to notice that these methods are not user-friendly, and implementing them requires technical knowledge of NTMPs. Expert systems like AHP based expert system, QFD based expert system, Hybrid method combination

Table 1 Shape application of NTMPs [10] conversion based on eleven-point scale [12]

	Holes				Through cavities		Surfacing		Through cutting	
Process	Precision small holes		Standard		Precision	Standard	Double contouring	Surface of revolution	Shallow	Deep
	Dia <0.025 mm	Dia >0.025 mm	L/D <20	L/D >20						
USM	–	–	0.665	0.335	0.665	0.665	0.335	–	0.335	–
AJM	–	–	0.50	0.335	0.335	0.50	–	–	0.665	–
ECM	–	–	0.665	0.665	0.50	0.665	0.665	0.50	0.665	0.665
CHM	0.50	0.50	–	–	0.335	0.50	–	–	0.665	–
EDM	–	–	0.665	0.50	0.665	0.665	0.50	–	0.335	–
EBM	0.665	0.665	0.50	0.335	0.335	0.335	–	–	–	–
LBM	0.665	0.665	0.50	0.335	0.335	0.335	–	–	0.665	0.50
PAM	–	–	0.50	–	0.335	0.335	–	0.335	0.665	0.665

Table 2 Material applications for metals and alloys [6] conversion based on eleven-point scale [12]

Process	Aluminum	Steel	Super alloy	Titanium	Refractory material	Ceramics	Plastic	Glass
USM	0.335	0.50	0.335	0.50	0.665	0.665	0.50	0.665
AJM	0.50	0.50	0.665	0.50	0.665	0.665	0.50	0.665
ECM	0.50	0.665	0.665	0.50	0.50	NA	NA	NA
CHM	0.665	0.665	0.50	0.50	0.335	0.335	0.335	0.50
EDM	0.50	0.665	0.665	0.665	0.665	NA	NA	NA
EBM	0.50	0.50	0.50	0.50	0.665	0.665	0.50	0.50
LBM	0.50	0.50	0.50	0.50	0.335	0.665	0.50	0.50
PAM	0.665	0.665	0.665	0.50	0.335	NA	NA	NA

Table 3 Economics of the various NTMPs [15] conversion based on eleven-point scale [12]

Process	Capital cost	Tooling cost	Power consumption cost	Material removal rate efficiency	Tool wear
USM	0.335	0.335	0.335	0.665	0.50
AJM	0.255	0.335	0.335	0.665	0.335
ECM	0.745	0.50	0.50	0.335	0.255
CHM	0.50	0.335	0.665	0.50	0.255
EDM	0.50	0.665	0.335	0.665	0.665
EBM	0.665	0.335	0.335	0.745	0.255
LBM	0.335	0.335	0.255	0.745	0.255
PAM	0.255	0.335	0.255	0.255	0.255

of AHP and TOPSIS, Decision tree-based expert system, Diagraph-based expert system and online knowledge-based fuzzy expert system are discussed to verify the selection methods implemented and to observe the limitations in the processes.

Chen [5] generalized the notion of bipolar fuzzy sets (FSs) to m-polar FSs. In a m-polar FS, the element's membership value ranges over $[0, 1]^m$ interval, representing all the m features of the element (Akram [1]). These FSs are fit for numerous real-life problems wherein information arrives from n agents ($n \geq 2$). The m-polar FSs have been largely used while modeling real-world problems which often involve multi-index, multi-object, multi-agent, multi-attribute, limits and/or uncertainty. These multipolar data further complicate the decision-making procedure in realistic scenarios thus initiating the multi-criteria decision-making (MCDM) problem. In resolving a MCDM task, the three preliminary steps to be followed include problem identification through determining the probable alternatives, assessment of alternatives depending on the condition provided by the decision-maker or decision-making experts and finally selection of the desired or best alternative. The m-polar FSs have been very effective tools in managing MCDM problems.

Table 4 Comparison of various methods for NTMPs Selections

	Flexibility	Computational time	Programming complexity	Decision maker's involvement	Type of data
Genetic algorithm	Medium (lack of learning ability)	High	High	High	Numerical
Artificial Neural network	High	High	Medium	Medium	Numerical
Simulated annealing	Medium	Medium	High	High	Numerical
Expert system	Medium	Medium	Medium	High	Both numerical and textual
CBR	High	Low	Low	Medium	Both numerical and textual

Table 5 Measure of NTM process selection attribute [12]

NTM selection attribute qualitative measure	Assigned value
Exceptionally low	0.0450
Extremely low	0.1350
Very low	0.2550
Low	0.3350
Below average	0.4100
Average	0.5000
Above average	0.5900
High	0.6650
Very high	0.7450
Extremely high	0.8650
Exceptionally high	0.9550

Research Gap

- Available expert systems for selecting non-traditional machining do not consider subgroup of variables for selection of best NTM process; the m-polar fuzzy set algorithm considers multipolar information (variables with subgroups).
- The m-polar fuzzy algorithm considers the percentage value of variables as input; it needs improved scaled information to the algorithm. Therefore, an eleven-point scale was used to present variables systematically.

Table 6 Existing non-traditional machining process selection systems with their limitations

Sr. No	Name of expert system	Selection method	Limitations	Author
1	Analytical Hierarchy process-based Expert System	The preference index value for the process	It is not made user friendly and needs technical knowledge of NTMPs in assigning priority values	[3]
2	Quality function deployment—based expert system	Overall scores obtained from weights of processes	It does not deal with multi-polar information	[4]
3	Multi-Attribute selection procedure-based expert system	It uses a combination of AHP and TOPSIS	It is not made user friendly, and the selection procedure is complex	[14]
4	Decision Tree-Based expert system	Depth-first search algorithm supported by utility functions	It does not deal with multi-polar information	[8]
5	A Diagraph- based expert system	Calculating the relative importance of different attributes affecting the NTMPs selection decision using pair-wise comparison matrices	It does not deal with multi-polar information	[7]
6	Online Knowledge-based Fuzzy Expert System	To calculate the outputs min–max method and weighted-centroid method are used in the system	It does not deal with multi-polar information	[14]
7	QFD-based NTM process selection framework	To automate the NTM process selection procedure with the help of graphical user interface and visual decision aid, Decision-making model in Visual BASIC 6.0	It does not deal with multi-polar information	[11]
8	PROMETHEE- GAIA method	It Used PROMETHEE-GAIA method, which is a visual aid to the decision engineers	It does not deal with multi-polar information	[9]

- The m-polar fuzzy set algorithm is used to solve various industry problems. However, it is not implemented for the selection of a non-traditional machining process.

2 Research Methodology

Research methodology followed to solve selection problem with the m-polar fuzzy set algorithm is explained below step by step.

Sr. No.	Steps to be followed [2]
1	Input A as Alternatives available
2	"P" as a input variable set
3	We are defining multipolar fuzzy soft relation R: A → P as per the alternatives and variables
4	The decision-maker requirement gives multipolar fuzzy subset Q over P, an optimal standard decision object
5	$\underline{R}(Q)$ and R(Q) calculate multipolar soft, rough approximation operators
6	Evaluate choice set $C = \underline{R}(Q) \oplus R(Q)$
7	Select the optimal decision O_k

2.1 Selection of a NTM Process for Non-metals to Obtain Through Cavities

The selection of the NTM process to obtain through cavities in non-metals with the optimum cost is a decision-making problem. Since every process has different properties, the material for the application is essential for the non-traditional machining process. The number of factors that can be considered for selecting the good NTM process, based on the decision-maker's requirement such as good material, desirable through cavities and optimum cost. Suppose a person wants to select a non-traditional machining process for non-metals to achieve precision through cavities. There are four NTM alternatives available. The alternatives are $a_1 =$ USM, $a_2 =$ AJM, $a_3 =$ CHM, $a_4 =$ LBM. One can select the most suitable NTM process. The materials, through cavities and costs, are the variables for selecting a non-traditional machining process. In this case $A = \{a_1, a_2, a_3, a_4\}$ is set of four nontraditional machining processes under consideration and let $P = \{p_1, p_2, p_3\}$ set of parameters related to the nontraditional machining process in A, where,

"p_1" variable for the material,
"p_2" variable for the through Cavities,
"p_3" variable for the cost.

We present more features of these variables as follows:

- The "Material" of the nontraditional machining process includes Ceramics, Plastics, Glass.

Table 7 m-polar fuzzy linguistic decision matrix

R	p_1	p_2	p_3
a_1	(good, fair, good)	(good, good, poor)	(low, low, low)
a_2	(good, fair, good)	(poor, fair, poor)	(very low, low, low)
a_3	(poor, poor, fair)	(poor, fair, poor)	(medium, low, high)
a_4	(good, fair, fair)	(poor, poor, poor)	(low, low, very low)

- The "Through Cavities" of the Nontraditional machining process include Precision, Standard, rough.
- The "Cost" of the Nontraditional machining includes Capital cost, Tooling Cost, and Power Consumption cost.

Features of these variables are the "Material" of the NTM process including ceramics, plastics and glass. The "Through Cavities" of the NTM process include Precision, Standard and rough. Finally, the "Cost" of the NTM includes Capital cost, Tooling Cost and Power Consumption cost.

Suppose that Person explains the "Effective selection of non-traditional machining process" with 3-polar fuzzy soft relation R: A $\rightarrow$ P, as given below, Table 7 shows linguistic decision matrix for alternatives and parameters.

Table 8 gives eleven-point scale to convert linguistic variables into quantitative values, that can be used for writing decision matrix values in numbers.

Table 9 shows decision matrix for NTM process selection with numbers, combining Table 6 and Table 7.

Thus, R over A $\times$ P is 3-polar fuzzy soft relation, where material, through cavities and the cost of the operation are considered variables for the selection of NTM

Table 8 Quality scale for NTM process selection [12]

A qualitative measure of NTM selection attribute		Assigned value
Exceptionally low	Exceptionally poor	0.0450
Extremely low	Extremely poor	0.1350
Very low	Very poor	0.2550
low	Poor	0.3350
Below average	Below fair	0.4100
Average	Fair	0.5000
Above average	Above fair	0.5900
High	Good	0.6650
Very High	Very good	0.7450
Extremely high	Extremely good	0.8650
Exceptionally high	Exceptionally good	0.9550

Table 9 m-polar fuzzy decision matrix for NTM process selection

R	p_1	p_2	p_3
a_1	(0.665, 0.5, 0.665)	(0.665, 0.665, 0.335)	(0.335, 0.335, 0.335)
a_2	(0.665, 0.5, 0.665)	(0.335, 0.5, 0.335)	(0.255, 0.335, 0.335)
a_3	(0.335, 0.335, 0.5)	(0.335, 0.5, 0.335)	(0.5, 0.335, 0.665)
a_4	(0.665, 0.5, 0.5)	(0.335, 0.335, 0.335)	(0.335, 0.335, 0.255)

process. From the table, think "Material" of the non-traditional machining process $((a_1, p_1), 0.665, 0.5, 0.665)$ means that the non-traditional approach a_1 is suitable to the ceramics, fair to the plastics and good to the glass. Let us assume that the expert suggested the most favorable standard decision object Q, which can be shown as 3-polar fuzzy subset of R as follows:

$$Q = (p_1, 0.865, 0.745, 0.955), (p_2, 0.955, 0.745, 0.335), (p_3, 0.255, 0.335, 0.255).$$

From definition,

$\underline{Q}_r\,(a_1) = (0.665, 0.665, 0.665)$, $Q_r\,(a_1) = (0.335, 0.5, 0.335)$,
$\underline{Q}_r\,(a_2) = (0.745, 0.665, 0.665)$, $Q_r\,(a_2) = (0.665, 0.665, 0.335)$,
$\underline{Q}_r\,(a_3) = (0.5, 0.665, 0.335)$, $Q_r\,(a_3) = (0.665, 0.665, 0.5)$,
$\underline{Q}_r\,(a_4) = (0.665, 0.665, 0.665)$, $Q_r\,(a_4) = (0.665, 0.665, 0.745)$.

Now, 3-polar fuzzy soft rough approximation operators $\underline{R}(Q)$, $R(Q)$, respectively, are given by.

$\underline{R}(Q) = (a_1, 0.665, 0.665, 0.665),(a_2, 0.665, 0.665, 0.665),(a_3, 0.5, 0.665, 0.335),(a_4, 0.665, 0.665, 0.665)$,
$R(Q) = (a_1, 0.335, 0.5, 0.335),(a_2, 0.745, 0.665, 0.335),(a_3, 0.665, 0.665, 0.5),(a_4, 0.665, 0.665, 0.745)$.

These operators are very close to the decision alternatives y_n, $n = 1, 2, 3, 4$.

$\underline{R}(Q) \oplus R(Q) = (a_1, 0.7773, 0.8325, 0.7773),(a_2, 0.9146, 0.8878, 0.7773),(a_3, 0.8325, 0.8878, 0.6675),(a_4, 0.8878, 0.8878, 0.9146)$.

Thus, the Person will select the non-traditional process a_1 (USM) to obtain through cavities in non-metals because the most favorable decision in the choice set $\underline{R}(Q) \oplus R(Q)$ is a_1.

2.2 Selection of a NTM Process for Metals to Obtain Through Cavities

The selection of the NTM process for through cavities in non-metals with the optimum cost is a decision-making problem. Since every process has different properties, the material for the application is essential for the NTM. There are many factors to consider when selecting the right NTM process, whether we are looking for good material, desirable through cavities and optimum cost. Suppose a person wants to select a NTM process for non-metals to achieve precision through cavities. There are four alternatives in his mind. There are four non-traditional machining alternatives available. The alternatives are $a_1 =$ USM, $a_2 =$ AJM, $a_3 =$ CHM, $a_4 =$ LBM. One can select the most suitable NTM process. The materials, through cavities and costs, are the variables for selecting a NTM process. In this case $A = \{a_1, a_2, a_3, a_4\}$ is set of four nontraditional machining processes under consideration and let $P = \{p_1, p_2, p_3\}$ set of parameters related to the nontraditional machining process in A, where,

"p_1" variable for the material,
"p_2" variable for the through Cavities,
"p_3" variable for the cost.

We present more features of these variables as follows:

- The "Material" of the non-traditional machining process includes Aluminium, Steel, Titanium.
- The "Through Cavities" of the Nontraditional machining process include Precision, Standard, rough.
- The "Cost" of the Nontraditional machining includes Capital cost, Tooling Cost, and Power Consumption cost.

Suppose that Person explains the "Effective selection of nontraditional machining process" by forming a 3-polar fuzzy soft relation R: $A \rightarrow P$, which is shown below,

Table 10 shows linguistic decision matrix for alternatives and parameters.

Table 11 gives eleven-point scale to convert linguistic variables into quantitative values, that can be used for writing decision matrix values in numbers.

Table 12 shows decision matrix for NTM process selection with numbers, combining Tables 10 and 11.

Table 10 Fuzzy Linguistic decision matrix

R	p_1	p_2	p_3
a_1	(poor, fair, fair)	(good, good, poor)	(low, low, low)
a_2	(fair, fair, fair)	(poor, fair, poor)	(very low, low, low)
a_3	(good, good, fair)	(poor, fair, poor)	(medium, low, high)
a_4	(fair, fair, fair)	(poor, poor, poor)	(low, low, very low)

Table 11 Qualitative measure for NTM process selection [12]

A qualitative measure of NTM selection attribute		Assigned value
Exceptionally low	Exceptionally poor	0.0450
Extremely low	Extremely poor	0.1350
Very low	Very poor	0.2550
low	Poor	0.3350
Below average	Below fair	0.4100
Average	Fair	0.5000
Above average	Above fair	0.5900
High	Good	0.6650
Very High	Very good	0.7450
Extremely high	Extremely good	0.8650
Exceptionally high	Exceptionally good	0.9550

Table 12 Decision matrix for NTM process selection

R	p_1	p_2	p_3
a_1	(0.335, 0.5, 0.50)	(0.665, 0.665, 0.335)	(0.335, 0.335, 0.335)
a_2	(0.50, 0.50, 0.50)	(0.335, 0.5, 0.335)	(0.255, 0.335, 0.335)
a_3	(0.665, 0.665, 0.50)	(0.335, 0.5, 0.335)	(0.5, 0.335, 0.665)
a_4	(0.50, 0.50, 0.50)	(0.335, 0.335, 0.335)	(0.335, 0.335, 0.255)

Thus, R over A × P is 3-polar fuzzy soft relation in which materials, through cavities and cost of the operation, are considered variables for the non-traditional machining process. From the table, think "Material" of the non-traditional machining process ((a_1, p_1), 0.335, 0.50, 0.50) means that the non-traditional approach a_1 is suitable to the ceramics, fair to the plastics and good to the glass. Let us assume that the expert suggested the most favorable standard decision object Q, which is a 3-polar fuzzy subset of R as follows:

$$Q = (p_1, 0.865, 0.745, 0.955), (p_2, 0.955, 0.745, 0.335), (p_3, 0.255, 0.335, 0.255).$$

From definition,

$\underline{Q}_r\,(a_1) = (0.665, 0.665, 0.665)$, $Q_r\,(a_1) = (0.665, 0.5, 0.5)$,
$\underline{Q}_r\,(a_2) = (0.665, 0.665, 0.665)$, $Q_r\,(a_2) = (0.665, 0.665, 0.5)$,
$\underline{Q}_r\,(a_3) = (0.665, 0.665, 0.335)$, $Q_r\,(a_3) = (0.665, 0.5, 0.5)$,
$\underline{Q}_r\,(a_4) = (0.665, 0.665, 0.665)$, $Q_r\,(a_4) = (0.665, 0.665, 0.5)$,

Now, 3-polar fuzzy soft rough approximation operators $\underline{R}(Q)$, $R(Q)$, respectively, are given by.

$\underline{R}(Q)$ = (a_1, 0.665, 0.665, 0.665),(a_2, 0.665, 0.665, 0.665),(a_3, 0.665, 0.665, 0.335),(a_4, 0.665, 0.665, 0.665),
$\overline{R}(Q)$ = (a_1, 0.665, 0.5, 0.5),(a_2, 0.665, 0.665, 0.5),(a_3, 0.665, 0.5, 0.5),(a_4, 0.665, 0.665, 0.5).

These operators are very close to the decision alternatives y_n, n = 1, 2, 3, 4.

$\underline{R}(Q) \oplus \overline{R}(Q)$ = (a_1, 0.8878, 0.8325, 0.8325),(a_2, 0.8878, 0.8878, 0.8325),(a_3, 0.8878, 0.8325, 0.8325),(a_4, 0.8878, 0.8878, 0.8325).

Thus, the Person will select the non-traditional process a_2 (AJM) to obtain through cavities in non-metals because the most favorable decision in the choice set $\underline{R}(Q) \oplus \overline{R}(Q)$ is a_2.

3 Conclusion

A conceptual design of the multipolar fuzzy set is studied and implemented. Eleven-point scale is used to convert linguistic data of NTM processes compared to previous m-polar fuzzy set applications using data as a percentage of variables. Subgroups of variables are considered in the decision-making process. This approach helps solve the selection problem of the non-traditional machining process. Problem solved for non-metals resulted in the selection of USM as the best alternative. Problem solved for metals resulted in the selection of AJM as the best alternative. Previous work in this area shows the same results as obtained by the m-polar fuzzy set method. Further, this method is to be developed for exact uncertainty values in non-traditional machining processes.

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