

# Failure Analysis of Machine Component using MADM Technique

Shrikant Shukla\*, Ashutosh Dwivedi

Mechanical Engineering Department & Vindhya Institute of Technology and Science,  
Satna, Madhya Pradesh, India

## Abstract—

**A**dvance manufacturing and production technology play a significant role in the growth of a country's industrial growth and largely dictates the course of the economic system. Globalization and Liberalization with reformed industrial trade policies have made manufacturing a central element to address global competition.

Currently, many methods and techniques are being embraced in order to advance the production and manufacturing skill whose main goal is to accomplish the effect optimum and desirable product, along with the reasonable cost, superior quality, and the more important proper selection of material, tool and effective use of local resources. Therefore, Decision making in the manufacturing environment is a strategic topic, especially in connection with the complexity of driving forces and factors influencing manufacturing systems dynamic's

In this paper Advance manufacturing and production decision making tool MADM method has been used in order to recounting the failure behaviour of machine tools. Using this method proper selection of tool and operating can be done which result in developing optimum product. Moreover, also optimum parameter can be selected so that the effective decision can be taken and the repetition of experimental, material selection can be minimized and failure can be overcome. Using data of available literature MADM method has been applied to get selective sequential order (Result) and this result are compared with experimental as well as analytical work and shows good agreement with the literature..

**Keywords—** GTMA, Decision making, SAW value, Failure Analysis

## I. INTRODUCTION

Machine tool maintainability and reliability crucially affect the three components of competitiveness: cost, quality, and production or manufacturing time. Well-maintained machines are under superior tolerance limit, helps to reduce rework and scrap, and raise consistency and quality of the part. Additionally, such machine tools enhance uptime and yield high-quality parts, by this means reducing total manufacture cost. A machine tool is a complex system consisting of various subsystems/components, and failure of a machine tool may occur due to failure(s) occurring in any of the subsystems/components. The failure may be attributed to certain failure causes. The unplanned maintenance and arbitrary failure of the machine tool has a direct effect on the efficiency of any manufacturer or unit. The company, therefore, has to ensure that the machine tool purchased has a good reputation on maintenance grounds and/or ensure that the maintenance technicians are quick at repairs, and/or have a backup machine ready to take over.

Decision making in the production and manufacturing environment is a strategic topic, particularly in connection with the intricacy of driving forces and features influencing production as well as manufacturing systems dynamics. The decision-making exercise can be implemented in the production and manufacturing environment at different phases, if appropriate procedures are made offered to the manufacturing engineers, designers, production planners, in addition to managers. These aspects are considered in the paper using fuzzy MADM methods and graph theory.

## II. LITERATURE REVIEW

(Taraman (1974) performed an experiment designed to estimate the parameters of this empirical model. Balakrishnan and DeVries (1985) extended this analysis to allow sequential updating of parameter estimates and inclusion of prior information in the estimation procedure. Mazzuchi and Soyer (1989) noted that the empirical model proposed by Taraman (1974) accounted for the effect of the machine operating environment but failed to account for aging (or wear out) characteristics of the tool. To account for both aging and the characteristics of the machine operating environment, a proportional hazards model (PHM) was proposed to assess tool life. In specifying the PHM, a Weibull model was assumed for the baseline failure rate to incorporate aging of the tool, and the effect of machining environment, as specified by Taraman (1974), was used to modulate the baseline failure rate.

R.V Rao works on a methodology based on digraph and matrix methods is developed for evaluation of alternative flexible manufacturing systems. A 'flexible manufacturing system selection index' is proposed that evaluates and ranks flexible manufacturing systems for a given industrial application.

Iyer and Ukhidave [6] Tool failure rates depend on many factors such as speed, feed, material properties etc. An attempt is made here to study analytically the tool life with speed and time dependent failure rates.

Oraby [8] investigates During machining, the cutting edge is subjected to various forms of tool failure such as: progressive wear leading to plastic deformation; chipping; fracture or breakage. Force signals are highly valid carriers of information about the machining process and they are, hence, among the best alternatives for tool monitoring and diagnostic techniques if a proper manipulation technique is devised.

Lee and Seah [9] analyses with the increasing use of computer numerical control, there is a growing need to ensure a reliable system to optimise tool usage or tool wear

Ibrahim and Christine [10] presents Detection of tool failure is very important in automated manufacturing. In this study, tool failure detection was conducted in two steps by using Wavelet Transformations and Neural Networks (WT-NN)

Pawar and Rao [13] analyse the optimum selection of process parameters plays a significant role to ensure quality of product, to reduce the machining cost and to increase the productivity of any machining process using TLBO algorithm Asli and Inan [14] works on electrical discharge machining (EDM) parameters that offer the best adhesion at the interface of a machined titanium–porcelain composite. First of all, with Taguchi method, machining parameters that will be effective in the bonding strength as well as their interactions on each other were determined in the test

Gholam and Toloo [15] suggests new data envelopment analysis (DEA) models for input and output scaling in advanced manufacturing technology (AMT).

Yin [18] found that most existing methods focus on PD selection, PL determination, or UF recognition, with more or less limitations. Since the mold design parameters or attributes influence each other, it is necessary to develop a methodology to consider these in an integrated manner.

### III. METHODOLOGY

#### Simple Additive Method (SAW) –

This is also called the weighted sum method and is the simplest and still the widest used MADM method. Here each attribute is given a weight and the sum of all weights must be 1. Each alternative is assessed weights for regard to every attribute to reflect relative importance

$$P_i = \sum_{j=1}^M w_j (m_{ij})_{normal} \tag{1}$$

#### Weighted Product Method (WPM) –

This method is similar to SAW. The main difference is that, instead of addition in the model there is multiplication. The overall or composite performance score of an alternative is given by Equation 2

$$P_i = \prod_{j=1}^M [(m_{ij})_{normal}]^{w_j} \tag{2}$$

Where (m<sub>ij</sub>) is as measures of performance of alternatives and (w<sub>j</sub>) is a value of weights of attributes. (m<sub>ij</sub>)<sub>normal</sub> represents the normalized value of m<sub>ij</sub>, and P<sub>i</sub> is the overall or composite score of the alternative A<sub>i</sub>.

#### Methodology of GTMA

The main steps are given below:

Step 1: classify the relevant attributes and the alternatives engaged in the decision-making problem being considered. find the values of the attributes (A<sub>i</sub>) and their relative magnitude (a<sub>ij</sub>). An objective or subjective assessment, or its range, may be assigned to each identified attribute as a limiting value or threshold value for its approval for the considered decision-making problem. An alternative with each of its choice attributes, meeting the acceptance value, may be picked out. After selecting the alternatives, the main task in preferring the alternative is to see how it serves the considered attributes.

Step 2:

1. Develop the attributes digraph considering the identified pertinent attributes and their relative importance. The number of nodes shall be equal to the number of attributes considered in Step 1 above. The edges and their directions will be decided upon based on the interrelations among the attributes (a<sub>ij</sub>).
2. Develop the attributes matrix for the attributes digraph. This will be the M\*M matrix with diagonal elements as A<sub>i</sub> and off-diagonal elements as a<sub>ij</sub>.

<b>Attributes</b>	<b>GR</b>	<b>NF</b>	<b>TF</b>	<b>SF</b>	<b>DA</b>	<b>GT</b>
<b>GR</b>	A	-1	-1	-1	-1	-1
<b>NF</b>	0	A	-1	-1	-1	-1
<b>TF</b>	0	0	A	0	0	0
<b>SF</b>	0	0	-1	A	0	0
<b>DA</b>	0	0	-1	0	A	0
<b>GT</b>	0	0	-1	-1	-1	A

(3)

3. Obtain the permanent function for the attributes matrix, on the lines of Equation 4.

4. Substitute the values of A<sub>i</sub> and a<sub>ij</sub>, obtained in step 1, in above to evaluate the index for the short-listed alternatives.

$$\begin{aligned}
 &= \prod_{i=1}^M S_i + \sum_{i=1}^{M-1} \sum_{j=i+1}^M \dots \sum_{M=i+1}^M (c_{ij} c_{ji}) S_k S_l S_m S_n S_o \dots S_i S_m \\
 &+ \sum_{i=1}^{M-2} \sum_{j=i+1}^{M-1} \sum_{k=j+1}^M \dots \sum_{M=i+1}^M (c_{ij} c_{jk} c_{ki} + c_{ik} c_{kj} c_{ji}) S_l S_m S_n S_o \dots S_i S_M \\
 &k, \dots, M \neq i \\
 &+ [\sum_{i=1}^{M-3} \sum_{j=i+1}^M \sum_{k=j+1}^{M-1} \sum_{l=k+1}^M \dots \sum_{M=i+1}^M (c_{ij} c_{jk} c_{kl} + c_{ik} c_{kj} c_{jl}) S_l S_m S_n S_o \dots S_i S_M
 \end{aligned}$$

$$\begin{aligned}
 & k, \dots, M \neq pus \\
 & \sum_{i=1}^{M-3} \sum_{j=i+1}^M \sum_{k=j+1}^{M-1} \sum_{l=k+1}^M \dots \sum_{M=i+1}^M (c_{ij}c_{jk}c_{kl} + c_{ik}c_{kj}c_{ji})S_1S_mS_nS_o \dots S_tS_M] \\
 & k, \dots, M \neq pus \\
 & + [\sum_{i=1}^{M-2} \sum_{j=i+1}^{M-1} \sum_{k=j+1}^M \sum_{l=i+1}^{M-1} \sum_{m=l+1}^M \dots \sum_{M=i+1}^M (c_{ij}c_{jk}c_{kl} + c_{ik}c_{kj}c_{ji})S_1S_mS_nS_o \dots S_tS_M \\
 & k, \dots, M \neq pus \\
 & + \sum_{i=1}^{M-4} \sum_{j=i+1}^{M-1} \sum_{k=j+1}^M \sum_{l=i+1}^M \sum_{m=l+1}^M \dots \sum_{M=i+1}^M (c_{ij}c_{jk}c_{kl} + c_{ik}c_{kj}c_{ji})S_1S_mS_nS_o \dots S_tS_M] \\
 & k, \dots, M \neq pus \\
 & \sum_{i=1}^{M-4} \sum_{j=i+1}^{M-1} \sum_{k=j+1}^M \sum_{l=i+1}^M \sum_{m=l+1}^M \dots \sum_{M=i+1}^M (c_{ij}c_{jk}c_{kl} + c_{ik}c_{kj}c_{ji})S_1S_mS_nS_o \dots S_tS_M \\
 & k, \dots, M \neq pus \\
 & + [\sum_{i=1}^{M-3} \sum_{j=i+1}^{M-1} \sum_{k=j+1}^M \sum_{m=1}^{M-1} \sum_{n=m+1}^M \dots \sum_{M=i+1}^M (c_{ij}c_{jk}c_{kl} + c_{ik}c_{kj}c_{ji})S_1S_mS_nS_o \dots S_tS_M \\
 & k, 1, m, \dots, M \neq pus \tag{4} \\
 & + \sum_{i=1}^{M-5} \sum_{j=i+1}^{M-1} \sum_{k=i+1}^M \sum_{l=i+1}^{M-2} \sum_{m=i+1}^M \sum_{n=j+1}^M \dots \sum_{M=i+1}^M (c_{ij}c_{jk}c_{kl} + c_{ik}c_{kj}c_{ji})S_1S_mS_nS_o \dots S_tS_M] \\
 & k, 1, m, n, \dots, M \neq pus \\
 & + \sum_{i=1}^{M-5} \sum_{j=i+1}^{M-1} \sum_{k=i+1}^M \sum_{l=i+1}^M \sum_{m=i+1}^M \sum_{n=j+1}^M \dots \sum_{M=i+1}^M (c_{ij}c_{jk}c_{kl} + c_{ik}c_{kj}c_{ji})S_1S_mS_nS_o \dots S_tS_M] \\
 & k, 1, m, n, \dots, M \neq pus \\
 & + \dots
 \end{aligned}$$

5. Arrange the alternatives in the descending order of the index. The alternative having the highest value of index is the best choice for the decision-making problem under consideration.

6. Obtain the identification set for each alternative, using Equation /  $T_1 / T_2 / T_3 / T_4 / T_{51} + T_{52} / T_{61} + T_{62} / \dots$ . Where Let  $T_{ij}$  represent the total value of terms of the  $j$ -th sub-grouping of  $i$ -th grouping of the machinability function. In case there is no sub-grouping, then  $T_{ij} = T_i$ , i.e., total value of terms of the  $i$ -th grouping. The identification set for a work material for the given machining operation is given above

7. Evaluate the coefficients of dissimilarity and similarity using Equations

$$C_d = (1/Q) \left( \sum_{i=1}^{M-1} \sum_{j=i+1}^M \psi_{ij} \right) \tag{5}$$

where,  $Q = \text{maximum of } \sum_{i=1}^{M-1} \sum_{j=i+1}^M T_{ij} \text{ and } \sum_{i=1}^{M-1} \sum_{j=i+1}^M T'_{ij}$

and  $C_s = 1 - C_d$ . List also the values of the coefficients for all possible combinations.

8. Document the results for future analysis/reference.

Step 3: Take a final decision, keeping practical considerations in mind. All possible constraints likely to be experienced by the user are looked into during this stage. These include constraints such as: availability or assured supply, management constraints, political constraints, economic constraints, environmental constraints, etc. However, compromise may be made in favor of an alternative with a higher index.

#### IV. RESULT AND DISCUSSION

##### Validation of Result

Manshadi et al. (2007) [12] proposed a numerical method for materials selection combining nonlinear normalization with a modified digital logic method

Table 1 Objective data of the Material attributes

Material	TI	YS	YM	D	TE	TC	SH
1	75.5	420	74.2	2.8	21.4	0.37	0.16
2	95	91	70	2.68	22.1	0.33	0.16

3	770	1,365	189	7.9	16.9	0.04	0.08
4	187	1,120	210	7.9	14.4	0.03	0.08
5	179	875	112	4.43	9.4	0.016	0.09
6	239	1,190	217	8.51	11.5	0.31	0.07
7	273	200	112	8.53	19.9	0.29	0.06

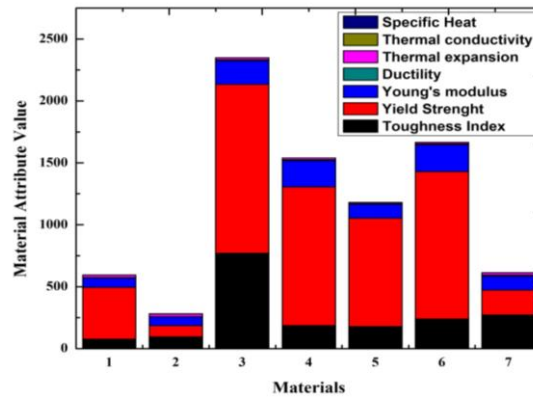


Figure 1 Shows relationship between material and with there attributes

From the figure 1 and table 1 shows the material attribute in a comparative way as shown in figure. From this we can conclude that the material is to selected should have better mechanical properties in failure analysis point of view during the tool failure analysis. Here material used are as follows: Material 1:Al 2024-T6; Material 2:Al 5052-O; Material 3:SS 301-FH; Material 4:SS310-3AH; Material 5:Ti-6Al-4V; Material 6:Inconel 718; Material 7:70Cu-30Zn

Table 2 Shows the Normalized data of the attributes

Material	TI	YS	YM	D	TE	TC	SH
1	0.0981	0.3077	0.3419	0.9571	0.4393	0.0432	0.375
2	0.1234	0.0667	0.3226	1	0.4253	0.0485	0.375
3	1	1	0.8709	0.3392	0.5562	0.4	0.75
4	0.2429	0.8205	0.9677	0.3392	0.6528	0.5333	0.75
5	0.2325	0.641	0.5161	0.6049	1	1	0.6667
6	0.3104	0.8718	1	0.3149	0.8174	0.0516	0.8571
7	0.3546	0.1465	0.5161	0.3142	0.4724	0.0552	1

The material selection index values of different materials are given below in descending order:

Table 3 shows the comparative result of different method

Material and Method value		
GTMA Method (Present)	MADM Method [12] (SAW Method)	MADM Method (WPM Method)
Material 3: SS 301-FH 39.1123	Material 3: SS 301-FH 0.4217	Material 3: SS 301-FH 0.6843
Material 5: Ti-6Al-4V 34.0554	Material 5: Ti-6Al-4V 0.5991	Material 5: Ti-6Al-4V 0.5248
Material 4: SS 310-3AH 30.6316	Material 6: Inconel 718 0.5352	Material 4: SS 310-3AH 0.4440
Material 6: Inconel 718 29.0377	Material 4: SS 310-3AH 0.5008	Material 6: Inconel 718 0.4412
Material 7: 70Cu-30Zn 20.0377	Material 1: Al 2024-T6 0.4217	Material 1: Al 2024-T6 0.2889
Material 1: Al 2024-T6 17.2897	Material 2: Al 5052-O 0.4020	Material 2: Al 5052-O 0.2505
Material 2: Al 5052-O 16.2634	Material 7: 70Cu-30Zn 0.3635	Material 7: 70Cu-30Zn 0.1809

From the above values of the material selection index, it is understood that the material designated as 3, i.e., SS 301-FH, is the right choice for the given problem of selection of a suitable material for a given problem by manshadi and the comparative same order of material is been proposed by SAW and MADM method is same but there resulted value is different because of different methodology technique.

Case 2

Table 4 Machine Tool Failure Data [16]

Machine tool	Speed (fpm)	Feed (ipr)	Depth of cut (inches)	Tool Life (min).
1	340	0.0063	0.021	70
2	570	0.0063	0.021	29
3	340	0.0141	0.021	60
4	570	0.01416	0.021	28
5	340	0.0063	0.021	64
6	570	0.0063	0.04	32
7	340	0.01416	0.04	44
8	570	0.01416	0.04	24
9	440	0.00905	0.029	35
10	440	0.00905	0.029	31
11	440	0.00905	0.029	38
12	440	0.00905	0.029	35
13	305	0.00905	0.029	52
14	635	0.00905	0.029	23
15	440	0.00472	0.029	40
16	440	0.01732	0.029	28
17	440	0.00905	0.0135	46
18	440	0.00905	0.0455	33
19	305	0.00905	0.029	46
20	635	0.00905	0.029	27
21	440	0.00472	0.029	37
22	440	0.01732	0.029	34
23	440	0.00905	0.0135	41
24	440	0.00905	0.0455	28

Table 5 Normalized data

Material tool	S	F	D	T
1	0.535433	0.363741	1	1
2	0.897638	0.363741	1	0.414286
3	0.535433	0.814088	1	0.857143
4	0.897638	0.817552	1	0.4
5	0.535433	0.363741	1	0.914286
6	0.897638	0.363741	1.904762	0.457143
7	0.535433	0.817552	1.904762	0.628571
8	0.897638	0.817552	1.904762	0.342857
9	0.692913	0.522517	1.380952	0.5
10	0.692913	0.522517	1.380952	0.442857
11	0.692913	0.522517	1.380952	0.542857
12	0.692913	0.522517	1.380952	0.5
13	0.480315	0.522517	1.380952	0.742857
14	1	0.522517	1.380952	0.328571
15	0.692913	0.272517	1.380952	0.571429
16	0.692913	1	1.380952	0.4
17	0.692913	0.522517	0.642857	0.657143
18	0.692913	0.522517	2.166667	0.471429
19	0.480315	0.522517	1.380952	0.657143
20	1	0.522517	1.380952	0.385714
21	0.692913	0.272517	1.380952	0.528571
22	0.692913	1	1.380952	0.485714
23	0.692913	0.522517	0.642857	0.585714
24	0.692913	0.522517	2.166667	0.4

Table 4 and table 5 Shows the machine tool failure data and normalized data to assess weights for each of the attributes to reflect its relative importance in the material selection decision is followed here. S,F,D,T are the attributes which denotes the speed, feed, depth of cut and at last tool life are considered here. The Attributes are ranked in order as per the importance here. Tool Life attribute is credited the 40, Speed is credited to 30, feed is credited with 20 and least important attribute Depth of cut is credited with 10.

The above case model is solve with GTMA method and the resulted data is been given below in tabulated manner with the choice as per rank.

Table 6 Resulted data of Case II

Material tool	Value	Choice as per rank
1	0.733378	5
2	0.607754	24
3	0.766305	1
4	0.692802	11
5	0.699092	9
6	0.715373	7
7	0.766045	2
8	0.760421	3
9	0.650473	16
10	0.627616	21
11	0.667616	15
12	0.650473	17
13	0.683836	13
14	0.674027	14
15	0.629044	20
16	0.705969	8
17	0.63952	19
18	0.717616	6
19	0.64955	18
20	0.696884	10
21	0.611901	22
22	0.740255	4
23	0.610949	23
24	0.689044	12

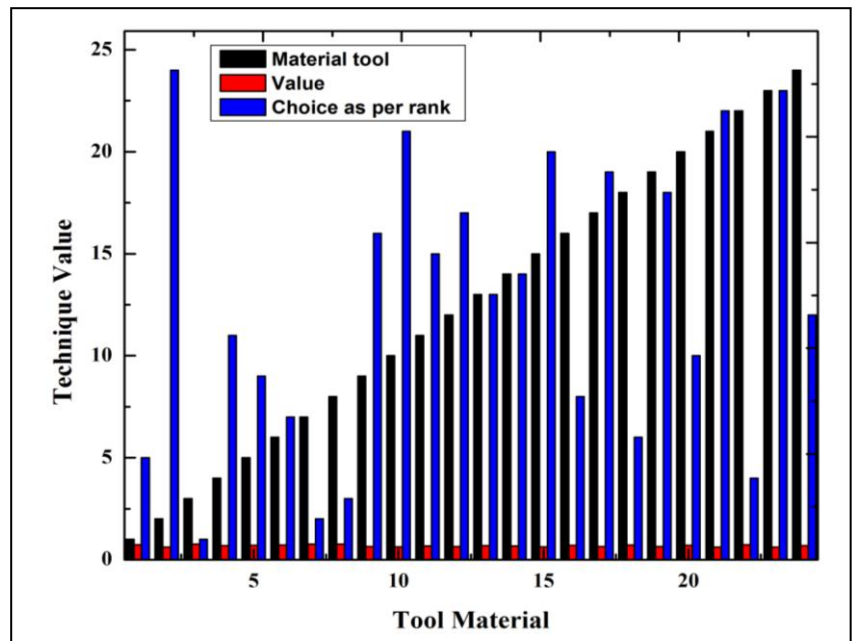


Figure 2 Shows graph between Material tool and GTMA value in concern with choice rank

**Case 3**

Wang [17] presented a real case of a machine group selection in a flexible manufacturing cell including two CNC milling machine groups, a CNC lathe, and a robot for material handling.

Table 7 Aim Data of Attributes of case 3

Alternative	Total Purchasing cost (\$)	Tool floor space m <sup>2</sup>	MN	Productivity*
1	581,818	54.49	3	5,500
2	595,454	49.73	3	4,500
3	586,060	51.24	3	5,000
4	522,727	45.71	3	5,800
5	561,818	52.66	3	5,200
6	543,030	74.46	4	5,600
7	522,727	75.42	4	5,800
8	486,970	62.62	4	5,600
9	509,394	65.87	4	6,400
10	513,333	70.67	4	6,000

MN: Total number of machines in a machine group of the flexible manufacturing cell  
\*Productivity (mm/min): the value corresponds to the machine with the slowest feed rate in the machine group

Table 8 Normalized data of the machine selection attributes of the example considered

Alternative	PC	FS	MN	Pr
1	0.83697995	0.83886952	1	0.859375
2	0.81781296	0.91916348	1	0.703125
3	0.83092175	0.8920765	1	0.78125
4	0.93159527	1	1	0.90625
5	0.86677536	0.86802127	1	0.8125
6	0.89676445	0.61388665	0.75	0.875
7	0.93159527	0.60607266	0.75	0.90625
8	1	0.72995848	0.75	0.875
9	0.95597907	0.69394261	0.75	1
10	0.94864347	0.64680911	0.75	0.9375

Table 8 and 7 shows the data attribute from which the normalized data is generated and as per the importance the attributes are credited and solve from which the choice of attributes is ranked and is shown in table 5.7 where SAW and GTMA data are well tabulated and ranked.

Table 9 Resulted Data of case 3

Alternatives	Index (SAW)	Alternatives	Index (GTMA)
4	0.430782	4	13.95523
9	0.40821	9	12.00903
8	0.39767	8	11.9258
5	0.395091	5	11.72268
10	0.394096	10	11.30164
1	0.394006	1	11.02021
3	0.386451	3	10.71783
7	0.383194	7	10.38811
2	0.375504	2	9.914436
6	0.373378	6	9.645792

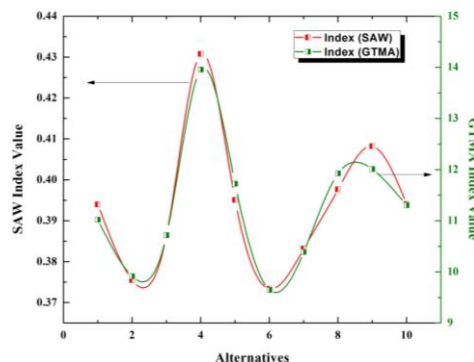


Figure 3 Shows the comparative graph between SAW and GTMA

From the above values of the machine selection index, alternative 4 is the best choice among the alternatives considered for the flexible manufacturing cell under the given conditions. The ranking of machines based on the proposed methodology is 4-5-1-3-2-9-8-10-7-6; the ranking presented by Wang [17] was 4-5-3-1- 2-8-9-10-7-6. The above results suggest the selection of alternative 4 for the FMC as the first right choice, alternative 5 as the second right choice, and alternative 6 as the last choice. These results are consistent with those presented by Wang et al. (2000). However, the ranking of certain alternatives obtained by using the proposed procedure is different from that proposed by Wang [17].

**Case 4**

Ching-Kao and Lu [1] proposed orthogonal array with gray–fuzzy logic method to optimize the side milling process with multiple performance characteristics. This example problem is related with selection of suitable cutting parameters in side milling process. The cutting parameters selection problem considers nine alternatives and two attributes, and the data are given in Table 10

Table 10 Quantitative data of the factors of example Ching-Kao and Lu [1]

V(rpm)	F(mm/t)	Da (mm)	Dr (mm)	cutting time	MRR	
					TWR (mm/min)	(mm <sup>3</sup> /s)
1,500	0.0592	7	0.4	281.53	1.2574*10 <sup>-4</sup>	16.58
1,500	0.074	11	0.7	225.23	1.7760*10 <sup>-4</sup>	56.98
1,500	0.0888	15	1	187.69	1.7582*10 <sup>-4</sup>	133.2
2,000	0.0592	15	0.7	211.15	2.2022*10 <sup>-4</sup>	62.16
2,000	0.074	7	1	168.92	2.0070*10 <sup>-4</sup>	51.8
2,000	0.0888	11	0.4	140.77	2.7918*10 <sup>-4</sup>	39.07
2,500	0.0592	11	1	78.04	5.8431*10 <sup>-4</sup>	65.12
2,500	0.074	15	0.4	135.14	3.0412*10 <sup>-4</sup>	44.4
2,500	0.0888	7	0.7	112.61	3.1436*10 <sup>-4</sup>	43.51

Table 11 Normalized data of Quantitative data of the factors of example Ching-Kao and Lu [1]

No.	V	F	Da	Dr	CT	TWR	MRR
1	0.6	1	7	0.4	1	1	0.124474
2	0.6	0.074	11	0.7	0.800021	0.707995	0.427778
3	0.6	0.0888	15	1	0.666679	0.715163	1
4	0.8	0.0592	15	0.7	0.750009	0.570974	0.466667
5	0.8	0.074	7	1	0.600007	0.626507	0.388889
6	0.8	0.0888	11	0.4	0.500018	0.45039	0.293318
7	1	0.0592	11	1	0.2772	0.215194	0.488889
8	1	0.074	15	0.4	0.48002	0.413455	0.333333
9	1	0.0888	7	0.7	0.399993	0.399987	0.326652

Table 12 Resulted comparative data of case model 3

Alternatives	Values (SAW)	Alternatives	Values fuzzy method	Alternatives	GTMA
3	0.44979	3	0.9651	3	1.79916
2	0.454309	2	0.5527	2	1.817236
1	0.686065	4	0.5163	1	2.74426
4	0.415056	5	0.4935	4	1.66024
5	0.406158	8	0.3877	5	1.624632
8	0.297483	6	0.382	8	1.189932
6	0.281633	9	0.3806	6	1.126532
9	0.298715	1	0.3744	9	1.19486
7	0.290656	7	0.3551	7	1.162624

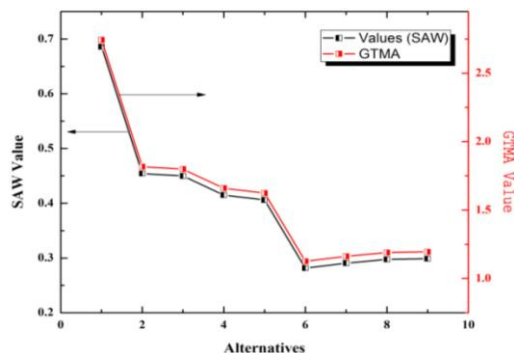


Figure 4 Shows the comparative graph between SAW and GTMA

From the above values and figure 4, it is understood that the cutting parameter designated as alternative 3, is the right choice for the given problem of selection of a suitable cutting parameter for heavy cutting in side milling. The second choice is alternative 2, and the last choice is alternative 7. ranking of the alternatives can be arranged as: 3-2-1-4-5-8-6-9-7.

## V. CONCLUSION

The failure data have been collected and analysed systematically for several commonly used machine tools failure analysis. The critical sub-system has been identified for each type of machine tool based on number of failures and break down hours, by application of DIAGRAPH and MADDM methods.

- Almost in all the cases the principle mode of failure is damage of component and most of them are standard and bought-in components. The use of appropriate condition monitoring technique for monitoring the above critical sub-systems of the machine tools will be helpful in identifying and predicting the failures.
- The procedure discussed in above chapter is useful for designers of reliable machine tools, and practicing engineers involved in failure minimization of the operating machine tool, leading to improved productivity and cost minimization. Further, the proposed methodology helps in identifying areas of improvement, and minimizing the severity of failure causes, thereby leading to the development of a machine tool of increased reliability. The procedure is not only useful for the failure cause analysis of machine tools, but also for the failure cause analysis of any type of systems.
- From using this Novel Advance production and Manufacturing decision making tool that can be utilized anywhere in order to get optimum result as well as optimum parameter can be selected so that the effective decision can be taken and the repetition of experimental, material selection can be minimized and failure can be overcome.

## REFERENCES

- [1] Ching-Kao C, Lu HS (2007) The optimal cutting-parameter selection of heavy cutting process in side milling for SUS304 stainless steel. *International Journal of Advance Manufacturing Technology*, 2007, 34:440–447
- [2] Taraman, K. “Multi Machining Output—Multi-Independent Variable Turning Research by Response Surface Methodology,” *International Journal of Production Research*, 12, (1974), 233–245.
- [3] Balakrishnan, P., and DeVries, M. F., “Sequential Estimation of Machinability Parameters for Adaptive Optimatization of Machinability Data Base Systems,” *Journal of Engineering for Industry*, 27, (1985), 159–166.
- [4] Mazzuchi, T. A., and Soyer, R., “Assessment of Machine Tool Reliability Using a Proportional Hazards Model,” *Naval Research Logistics*, 36, 1989, 765–777.
- [5] R.Venkata Rao “A decision-making framework model for evaluating flexible manufacturing systems using digraph and matrix methods”, *The International Journal of Advanced Manufacturing Technology* October 2006, Volume 30, Issue 11-12, pp 1101-1110
- [6] K.S.S. Iyer, V.H. Ukhidave “Tool life with speed and time dependent failures, *Computers in Industry*”, Volume 2, Issue 2, June 1981, Pages 141-145.
- [7] R. Venkata Rao, decision making in the manufacturing Environment, *Springer*, ISBN-13: 9781846288180
- [8] S.E. Oraby, “Monitoring of turning operation via force signals Part 1: Recognition of different tool failure forms by spectral analysis”, *Wear*, Volume 184, Issue 2, May 1995, Pages 133-143.
- [9] K.S Lee, K.H.W Seah, Y.S Wong, Lenny K.S Lim, “In-process tool-failure detection of a coated grooved tool in turning”, *Journal of Materials Processing Technology*, Volumes 89–90, 19 May 1999, Pages 287-291.
- [10] Ibrahim Nur Tansel, Christine Mekdeci, Charles McLaughlin, “Detection of tool failure in end milling with wavelet transformations and neural networks (WT-NN)”, *International Journal of Machine Tools and Manufacture*, Volume 35, Issue 8, August 1995, Pages 1137–1147
- [11] Decision Making In manufacturing Environment by R. Venkata Rao Springer 2007
- [12] Manshadi BD, Mahmudi H, Abedian A, Mahmudi R , “A novel method for materials selection in mechanical design: combination of non-linear normalization and a modified digital logic method”. *Materials & Design* 28,2007,8– 15
- [13] P. J. Pawar, R. Venkata Rao , “Parameter optimization of machining processes using teaching–learning-based optimization algorithm”. *The International Journal of Advanced Manufacturing Technology* July 2013, Volume 67, Issue 5-8, pp 995-1006
- [14] Asli Secilmis, A. Murat Olmez, Murat Dilmec, H. Selcuk Halkaci, Ozgur Inan, “Determination of optimal EDM machining parameters for machined pure titanium-porcelain adhesion” *The International Journal of Advanced Manufacturing Technology*, November 2009, Volume 45, Issue 1-2, pp 55-61
- [15] Gholam R. Amin, Mehdi Toloo, M. Sheikhan, “Input and output scaling in advanced manufacturing technology: theory and application” *The International Journal of Advanced Manufacturing Technology* October 2010, Volume 50, Issue 9-12, pp 1235-1241
- [16] Jason R. W. Merrick and Re’ k Soyer, “A Bayesian Semiparametric Analysis of the Reliability and Maintenance of Machine Tools” *American Statistical Association and the American Society for Quality technometrics*, february 2003, vol. 45, no. 1
- [17] Wang T, Shaw CF, Chen YL, “Machine group selection in flexible manufacturing cell: a fuzzy multiple attribute decision-making approach”. *International Journal of Production Research* 38:2079–2097
- [18] Yin ZP, Ding H, Li HX, Xiong YL, “Geometric moldability analysis by geometric reasoning and fizzy decision making”. *Computer Aided Design* 2004, 36:37-50