FUZZY MODELLING AND GA OPTIMIZATION FOR OPTIMAL SELECTION OF PROCESS PARAMETERS TO MAXIMIZE MRR IN ABRASIVE WATER JET MACHINING

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Abstract- Abrasive water jet machining process is a mechanical type advanced machining process, which is widely used because of inherent advantage to cut electrically non-conductive as well as difficult-to-machine materials more rapidly and efficiently. The present work addresses modeling and optimization of the process parameters for this machining technique. To model the process a set of experimental data has been used to predict the depth of cut for various process parameters such as water jet pressure, jet traverse rate and abrasive flow rate at five levels each, in machining black granite material. A fuzzy model is built with the knowledge base formed by means of experimental data to predict the depth of cut achievable with a set of process parameters. The fuzzy model is then embedded into a Genetic algorithm to optimize the process parameters to maximize material removal rate (MRR).

Index Terms— Abrasive water jet machining, Fuzzy logic modeling, Depth of cut, Genetic algorithm, Optimization.

Notations—

$A_{water\ jet\ pressure}$	**Bit length of binary code for water jet pressure**
$A_{traverse\ rate}$	**Bit length of binary code for jet traverse rate**
$A_{abrasive\ flowrate}$	**Bit length of binary code for abrasive flow rate**
d	**Depth of cut**
F	**Fitness function**
F_{avg}	**Average Fitness function**
p_select	**Probability of selection**
p_cross	**Probability of cross over and the**
p_mut	**Probability of mutation**
MRR	**Material removal rate**
DOE	**Design of Experiments**

I. INTRODUCTION

Abrasive water jet machining process is a mechanical type advanced machining process which uses kinetic energy of abrasive particles flowing along with water jet for machining electrically non-conductive as well as difficult-to-machine materials comparatively more rapidly and efficiently. It has several distinguished advantages. It is non-contact inertialess high machining process to produce, narrow kerf on material without any thermal and deformation stresses. It has Multi-directional cutting capacity with high flexibility and small cutting forces. With this recycling of abrasive particles is possible [1], [2].

Various process parameters as shown in Fig 1 have a great influence on the quality of the machined components. The quality measures include depth of cut, kerf width and its regularity and surface finish. Therefore it is important to study the effects of process parameters on the output parameters. If cutting has to be done in one pass then the depth of cut is a known parameter, and therefore it is considered as a process output parameter.

To model and optimize the process parameters in AWJM considering different objectives such as high MRR, good quality cut, low cost of machining, lower consumption of abrasives, etc., extensive experimentation is required. This tedious experimentation was avoided by employing different approaches like DOE, analytical models, empirical and semi-empirical models, etc. An analytical model requires an understanding of basic micro-cutting mechanism, the role of cutting forces, the particle trajectories as a function of angle and velocity of impact and kinematic equations. Moreover, these models make several assumptions. Hence, such models cannot be employed satisfactorily for complex processes like AWJM [1], [2]. Empirical and semi-empirical models are formulated with experimental data available or obtained by conducting experiments. Kolahan and Khajavi [2] used Taguchi method and regression modeling to predict depth of cut from input process parameters in cutting 6063-T6 aluminum alloy. For checking the adequacy they used analysis of variance (ANOVA) technique. Wang [3] used dimensional analysis technique to build predictive model for depth of cut in AWJ contouring of alumina ceramics. Hashish [4], [5] developed a mathematical model to relate process parameters setting to the process output variables in waterjet technique. These empirical relations are only applicable to the process parameters within a particular range. The use of DOE reduces the number of experiments, but they require tools like regression analysis to build a definite relation between desired parameters [6]. Again this requires regression coefficient, which constrains the use of model to that particular range of process parameters.

Limitations of these models shows that there is need to develop the model which can be built with limited experimentation, provides enough flexibility to extend other ranges of operations and should not depend on any process related assumptions.

Kovacevic and Fang [7] developed a model based on fuzzy rules to suggest the combination of AWJM parameters like water jet pressure, traverse rate and abrasive flow rate to predict depth of cut in AWJ milling operations. Their model considered nozzle inside diameter as an input parameter. These parameters were determined by employing an iterative procedure. The iterative procedure may not give optimal set of combination of parameters for cutting material to particular depth of cut. Moreover, fuzzy rules are used as decision-making tool rather than search technique for optimization [8]. Chakravarthy and Babu [1] built a model based on fuzzy principle and combined with genetic algorithm to choose best combination among several combinations of process parameters obtained from fuzzy model. They made an attempt to develop fuzzy model combined with genetic algorithm to select best combination of process parameters in machining the material of any desired thickness with AWJM to maximize Material Removal Rate (MRR).

II. THEORY

A. Fuzzy Logic

Fuzzy Logic (FL) is a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Fuzzy logic is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with vague boundaries in which membership is a matter of degree. In Fuzzy logic, truth value of propositions is determined by degree of membership which can be anywhere between 0 and 1. A fuzzy set F, can be defined as {x, ¼A(x) | x X} where, x is the element of Universe of Discourse X and ¼A(x) is the degree of membership. The fuzzy set in Universe of Discourse is expressed by membership functions like Piece-wise linear functions, Gaussian distribution function, Sigmoid curve and Quadratic and cubic polynomial curves. The structure of fuzzy inference system (FIS) is shown in Fig 2. FIS consists of four basic modules such as,

(a) Fuzzification
(b) Knowledge base
(c) Inference from knowledge base
(d) Defuzzification

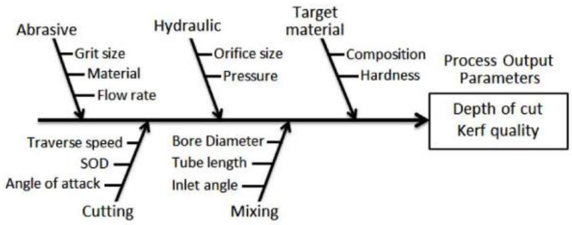

Fig. 1 Influence of process parameters for Abrasive Water Jet Machining

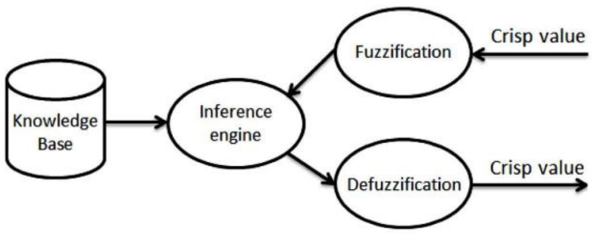

Fig. 2 Structure of fuzzy inference system

The fuzzification module converts crisp input value into a degree of membership. This fuzzified value is given as input to the inference engine, where it processes based on knowledge base formed from fuzzy rules and data base to generate fuzzy output. Then this fuzzy output is converted back to crisp value in the defuzzification module by using various defuzzification methods like centroid calculation, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum, and smallest of maximum, etc. [9].

B. Genetic Algorithms

Genetic algorithm (GA) is a computerized search and optimization algorithm based on the mechanics of natural genetics and natural selection, which are more robust and more likely to locate global optimum. Genetic algorithm needs design space to be converted into genetic space.

Therefore, GA works with a coding of variables. The advantage of working with a coding of variable space is that coding discretizes the search space even though the function may be continuous. A difference between GA and most of the traditional optimization methods is that a GA uses the population of points at one time instead of single point at a time as in traditional optimization methods. This means that GA processes a number of designs at the same time. GA uses randomized operators, which improve the search space in an adaptive manner to determine global optimum solution. GA is an iterative procedure which evolves an optimal candidate solution from a fixed population of candidates chosen randomly at the initial stage. After each iteration, known as generation, new population is generated, known as offspring, based on the fitness of each candidate solution which is estimated with the fitness function. The process of generating a new population is called reproduction [10].

In GA, a candidate solution is represented by a chromosome or a string. The value of chromosome is determined by a fitness function, which is related to the objective function. The chromosomes with high fitness value form new population. To search entire populations various GA operators like cross over, mutation, etc. are used. Crossover operator exchanges some part of two chromosomes to generate new offspring. Mutation operator provides a small randomness to newly generated offspring's from crossover operator. The mutation operator is also used to maintain diversity in the population. After crossover and mutation operations, the strings for next generation are selected based on the survival of the fittest principle. This process is repeated for number of times to achieve the optimal population set [11].

III. METHODOLOGY

In present work, the GA uses fuzzy model to predict depth of cut and then to find best combination of process parameters like water jet pressure, abrasive flow rate and traverse rate to cut material up to desired depth by AWJM process. Flow chart for the procedure followed is shown in Fig 3. The GA randomly generates initial set of for water jet pressure, abrasive flow rate and traverse rate. These randomly generated values are then supplied to fuzzy model as an input to predict depth of cut. Then with the values of predicted depth of cut and desired depth of cut, the predicted error is estimated. This process is repeated for number of generations until the predicted error falls within user defined error. The combination of water jet pressure, abrasive flow rate and traverse rate, that gives the minimum error is chosen as best combination for machining the material of given depth with AWJM.

The database required to build fuzzy model is obtained by conducting experiments by varying each of three process parameters at five different levels. These experiments were conducted by selecting the set process parameters randomly. The set of values for different process parameters and data related to other parameters is given as below,

Water jet pressure (MPa)	60,130, 200, 270, 350
Abrasive flow rate (kg/min x 10-3)	30, 50, 90, 130, 170
Traverse rate (mm/min)	30, 70, 150, 230, 325
Stand-off distance (mm)	3
Abrasive type and size	garnet, 80 mesh size
Primary nozzle diameter (mm)	0.25
Secondary nozzle diameter (mm)	0.8
Number of passes	one
Angle of cutting	90^0

Fig 4a shows the cross-section of black granite used for the experimental study. This particular cross-section was chosen to determine the exact depth of penetration of water jet into the material by employing different process parameters during the experiments. With each set of process parameters, the jet is activated away from edge and stopped when jet splashing was occurred. The depth of penetration of jet was estimated using relation d = L sin(y), where y is angle

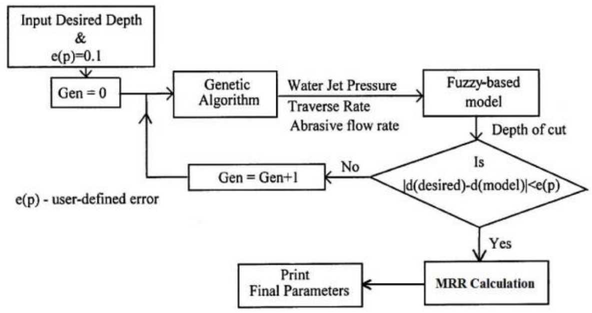

Fig. 3 Flowchart for proposed approach employing GA and fuzzy logic

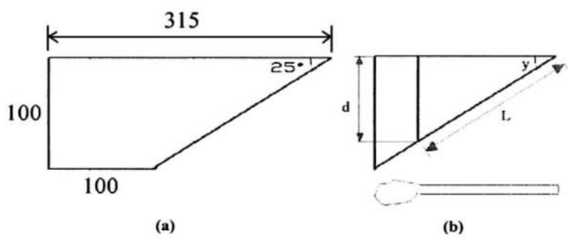

Fig. 4 a) Geometry of work material, b) estimation of depth of penetration of jet

between slant surface and top surface of specimen and L is length of cut along slant surface as shown in Fig 4b.

To cut material precisely, good quality of surface is important. Thus, the depth up to which kerf width is uniform is considered. According to vales chosen for different process parameters indicated earlier, 125 experiments were conducted. This experimental results show that, the depth of cut varies between 0.0 – 52.69 mm.

IV. DEVELOPMENT OF FUZZY MODEL

A. Fuzzification Model

The fuzzification module deals with the conversion of crisp values of input/output process parameters into the degree of membership, with the help of various membership functions such as triangular, trapezoidal, quadratic, etc. employed for representing universe of discourse. In present work, triangular function was chosen because of its ease of construction. Generally, triangular functions need not be symmetric and equally spread over given ranges. The selection of number of triangles depends on the complexity of the problem and density of data points in the region of interest [1].

In the present work, the input parameters such as water jet pressure, abrasive flow rate and traverse rate are divided into five levels and output parameter depth of cut is divided into 11 levels, as shown in Fig 5. Most of values for depth of cut are falls in range of 0 – 30 mm, supports the more number of triangles in range of 0 – 30 mm. The input and output parameters are defined with the help of linguistic terms such as high, medium, low, etc. The universe of discourse, along with the linguistic variables for each variable is shown in Fig 5.

From the triangular membership function, the degree of membership for each of the input and output process parameters can be determined from its crisp value, with the help of the following relation.

$$\mu_{LV}(a) = \frac{a-l}{q-l} \qquad for \;\; l \le a \le q$$

$$\mu_{LV}(a) = \frac{u-a}{u-q} \qquad for \;\; q \le a \le u$$

Where,
LV = linguistic variable under consideration
μ = degree of membership
l = lover limit value for process parameter for a perticular linguistic variable
u = upper limit value of process parameter for a perticular linguistic variable
q = (l + u)/2

B. Knowledge Base

In this module, 125 fuzzy rules are formed with the help of data available from 125 experiments conducted on black granite. These 125 rules form the knowledge base for the given problem, and acts as decision makers in predicting the depth of cut. A typical rule is formed as follows,

IF water jet pressure IS high AND traverse rate IS low AND abrasive flow rate IS very low THEN depth of cut IS medium.

C. Inference Model

The inference module scans the knowledge base to identify which rules are applicable for any given input and desired objectives. The rules act as decision makers in predicting the depth of cut for any given vales of water jet pressure, abrasive flow rate and traverse rate.

D. Defuzzification Model

The output of inference module is fuzzy in nature and it is necessary to convert it into crisp value for meaningful comparison. As mentioned earlier, out of various defuzzification methods, centroid method gives a value for depth of cut with minimum least-squares of error [12]. Thus, centroid method is employed in the present work. This method is illustrated with an example.

Consider a water jet pressure of 185 MPa, jet traverse rate of 100 mm/min and abrasive flow rate of 0.150 kg/min as input process parameters. During fuzzification water jet pressure falls in the category of very high with degree of membership 0.80. The jet traverse rate falls into two categories of low and medium with degree of membership of 0.74 and 0.20 respectively. Similarly abrasive flow rate falls into the categories of high and very high with degree of membership 0.58 and 0.58 respectively. This combination of input parameters activates four different rules in knowledge base.

They are:

Rule 87: IF water jet pressure IS medium (0.80) AND jet traverse rate IS low (0.74) AND abrasive flow rate IS high (0.58) THEN depth of cut IS low.

Rule 88: IF water jet pressure IS medium (0.80) AND jet traverse rate IS medium (0.20) AND abrasive flow rate IS high (0.58) THEN depth of cut IS very low.

Rule 112: IF water jet pressure IS medium (0.80) AND jet traverse rate IS low (0.74) AND abrasive flow rate IS very high (0.58) THEN depth of cut IS medium.

Rule 113: IF water jet pressure IS medium (0.80) AND jet traverse rate IS medium (0.20) AND abrasive flow rate IS very high (0.58) THEN depth of cut IS low.

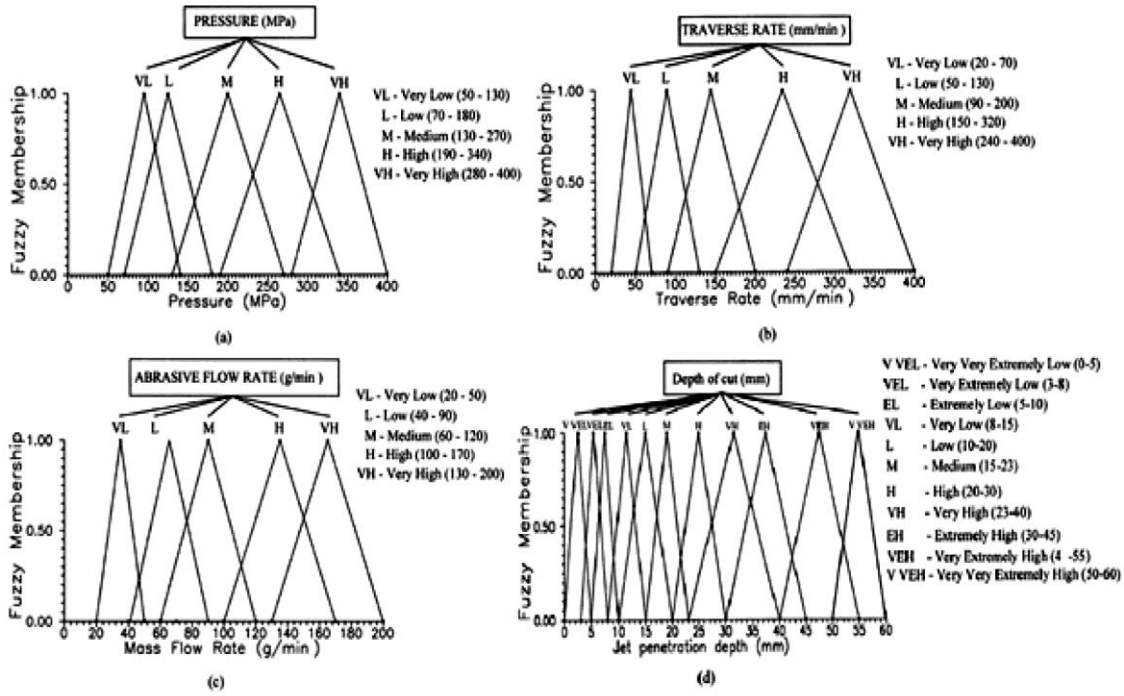

Fig. 5 Fuzzy membership functions for a) water jet pressure, b) traverse rate, c) abrasive mass flow rate and d) jet penetration depth

In centroid method, the corresponding firing strength for rules is determined by conjunction or minimum operator and these values are shown as,

For Rule 87: 0.80 $\wedge$ 0.74 $\wedge$ 0.58 = 0.58 of category 'low' of depth of cut
For Rule 88: 0.80 $\wedge$ 0.74 $\wedge$ 0.58 = 0.58 of category 'medium' of depth of cut
For Rule 112: 0.80 $\wedge$ 0.20 $\wedge$ 0.58 = 0.20 of category of 'very low' depth of cut
For Rule 113: 0.80 $\wedge$ 0.20 $\wedge$ 0.58 = 0.20 of category of 'low' depth of cut

To determine a single crisp value for the depth of cut by centroid method, the degrees of membership obtained are used to intersect corresponding triangular function for depth of cut. With 0.58 as degree of membership, the triangle with category 'low' is intersected. Similarly, other triangles are also intersected as shown in Fig 6. All these truncated triangles are then connected and centroid of resultant shape is considered as crisp vale for the depth of cut. In this particular case, depth of cut is obtained as 16.191 mm with the process parameters of 185 MPa, 100 mm/min and 0.150 kg/min.

E. Validation of Fuzzy Model

In order to validate the fuzzy model developed in the present work, the published results [1] and corresponding experimental values have been used (Table 1). The predicted depth of cut with respect to each set of process parameters has been presented in the table. The deviations of the predicted depths of cut, both published and present, from the experimental depths of cut have been evaluated. It can be observed from the table that, in majority of the cases, the predicted values with the present model are close to the experimental values. Further, the average deviation with the present model is found to be "-0.06%", whereas the reported values yield the average deviation as "4.17%". Therefore it is the clear indication that the present model is reliable in accurately predicting the depth of cut against the given set of process parameters.

V. AUTOMATIC SELECTION OF OPTIMAL PROCESS PARAMETERS USING GA

The model developed using fuzzy approach predicts the depth of cut depending on the input process parameters of AWJM process. But in practice, it is required to find the set of process parameters which are required to machine any material, to any desired depth of cut. Further to achieve a particular objective like maximizing material removal rate (MRR), the best combination of process parameters is required. Since, the selection of such optimal set is an iterative procedure which is quite tedious; GA is employed in the present work to reach at the best combination of process parameters.

In the proposed approach, GA is employed in combination with fuzzy approach to predict a set of process parameters to machine material to the desired depth of cut. The GA starts with a set of process parameters as an initial population. The size of initial population has influence on both performance and efficiency of GA. A small size of initial population may

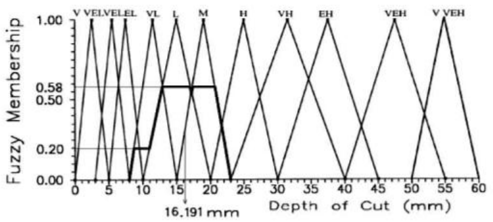

Fig. 6 Defuzzification of degree of membership into crisp value using centroid method

give premature convergence, whereas the larger size of initial population avoids the chance of premature convergence but it may take more time to get results. Reeves [13] suggested that the initial population can be in between one to two times the string length. Therefore, in present work the initial population is considered to be 32.

The random generator for generating initial population is selected in such way that the values of generated process parameters fall in the range of operation. Then the population of feasible process parameters forms the input to fuzzy model to predict the depth of cut. Then these predicted depths are compared with desired depth to estimate the deviation in the predicted depth. The chromosomes with minimum deviation in depth of cut are further subjected to various genetic operations in order to obtain best combination of process parameters.

In GA, the selection of the best combination of process parameters from initial population depends on maximizing fitness function (Fi). In this work, Fi is the difference between the maximum deviation noticed with predicted depth in total population and the deviation in predicted depth for the ith combination. A population size of six combinations used for illustration of proposed approach is shown in Table 2. The fitness function for all combinations in initial population is determined and is shown in Table 2. The probability of selection (p_select) is determined to decide which combinations are allowed to enter into the reproduction stage. The probability of selection is the ratio of individual fitness function (Fi) to the average fitness function (Favg). The number of combinations passed to reproduction stage is determined by considering integral part of p_select, as actual count. If number of combinations in reproduction stage is less than initial population, then the combination with larger decimal part of p_select is considered until the number of combinations becomes equal to the initial population as shown in Table 2.

The combinations entered into reproduction stage are further subjected to recombination operators like crossover and mutation. Binary values of process parameters are very efficiently and effectively used during recombination operators instead of decimal values. Therefore each combination of water jet pressure, traverse rate and abrasive flow rate is coded in form of binary string, with a string length of 9, 9 and 8 genes respectively. Thus, the total length of string contains 26 genes. This string length is decided based on the range and maximum value chosen for input process parameters.

Table 1 Comparison of depth predicted by fuzzy model with actual depth produced

Water jet pressure (MPa)	Traverse rate (mm/min)	Abrasive flow rate (kg/min x 10^{-3})	Depth of cut (mm)			Deviation of predicted depth of cut (%)	
			Experimental value	Reported value [1]	Predicted value	Reported [1]	Predicted
300	30	21	31	34	33.99	9.00	8.80
325	30	107.6	45	44	41.15	-2.20	-9.36
350	30	65.2	43	47	44.36	8.50	3.06
150	150	90	11	9.38	9.37	-1.72	-1.72
180	70	30	15	15	15	0.00	0.00
200	70	110	17	19	18.08	10.50	5.97
220	70	130	21	22.14	19.59	5.14	-7.20
Average deviation of predicted depth of cut (%)						4.17	-0.06

Table 2 Initial population and fitness values

Combination set number	Input parameter values			*Fi*	Probability of selecting combination, $p\_select = \frac{Fi}{Favg}$	Actual count	Additional count
	WP (MPa)	TR (mm/min)	AFR (g/min)				
1	257	204	154	13.65	1.55	1	1
2	314	307	70	2.49	0.28	0	0
3	313	117	122	10.81	1.23	1	0
4	335	309	187	20.64	2.34	2	0
5	147	228	192	3.06	0.35	0	0
6	298	307	154	4.42	0.50	0	1

Thus,
STR_LENGTH = Awater jet pressure + Atraverse rate + Aabrasive flowrate
Where A is string length of the corresponding input parameters.
A typical genetic string can be represented as,
101001110 | 100001100 | 10001101
334 MPa 268 mm/min 0.141 kg/min

The frequency of cross over and mutation depends upon the probability of crossover and the probability of mutation. If p_cross is high, more strings in the initial population will be subjected to crossover, allowing new structures to move more quickly to new population. If p_cross is too low, the chance of generating the new structures is low. This may give a local optimum due to the saturation of the search space with a low rate of exploration. The probability of cross over is normally selected to be in the range 0.6 - 0.9 [1]. In this work, the value for probability of crossover is considered as 0.9. A mutation operator is employed to avoid any loss of feasible solutions obtained after the crossover operation. Normally, the value of p_mut is selected to be very low since higher values may lead to negative effects in terms of discarding the best strings. Thus the values p_mut is considered as 0.1. The crossover mates are the strings of the population which undergo crossover operation to generate offsprings. The crossover sites are the sites at which crossover is done and the mutation site is the site at which mutation is done. The cross-over mates, cross-over sites and mutation sites are generated randomly. Although, string contains 26 genes, strings with 12 genes are considered to explain mechanism of crossover and mutation operation. The mechanism of two point crossover employed in present work along with offspring generated is shown in Fig 7. The mechanism of bit-flip mutation employed in present work is shown in Fig 8.

This mutant generated after recombination operators are decoded into decimal values for water jet pressure, traverse rate and abrasive flow rate. Then these values are taken as input to the fuzzy model to predict depth of cut. The predicted depth is compared with desired depth to estimate deviation and fitness value. The combination of process parameters with higher fitness value enter into next generation. The strategy of replacing weak solution in present generation with strong solution in previous generation is adopted, to ensure that only best solutions will be retained for next generation.

The above procedure is repeated for certain number of times to obtain the best combination of water jet pressure, traverse rate and abrasive flow rate which can give maximum Fi. This process gives several combinations for process parameters. Best combination of process parameters which will maximize Material Removal Rate (MRR) can be found out using following equation,

$$MRR = h * w * TR \quad (1)$$

Where, h is depth of cut up to uniform kerf width, w and TR is jet traverse rate. If assumes that, in Equation (1), the kerf width, w is equal to the secondary nozzle diameter or focusing tube diameter, dj

Then,

$$MRR = h * dj * TR \quad (2)$$

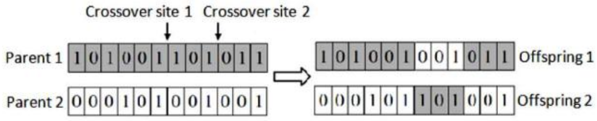

Fig. 7 Representation of two point crossover operator

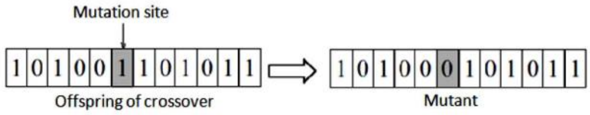

Fig. 8 Representation of Bit-flip mutation operator (l is length of string)

To maximize MRR, the value for TR should be maximum. Hence maximum values for the jet traverse rate among all feasible solutions obtained after GA is selected to calculate MRR in Equation (2). Therefore, Equation (2) is giving maximum MRR for cutting the material upto desired depth with best combination of process parameters obtained from GA.

VI. VALIDATION OF PROPOSED MODEL

The proposed approach is illustrated with example considering desired depth of 22 mm. The genetic parameters employed are: population size = 32, probability of crossover = 0.9 and probability of mutation = 0.1. With these settings, genetic approach gave optimal values after 69 generations. The values for water jet pressure, traverse rate and abrasive flow rate are 375 MPa, 128 mm/min and 122 * 10-3 kg/min respectively. With these values predicted depth of cut is 22.026 mm and MRR is 2.256 * 103 mm3/min. By employing the same process parameters, experiment was conducted on the same material and the depth achieved was 22.09 mm. Since, the user defined error is 0.1 mm and the predicted and experimental values of depth of cut are within this tolerance limit with desired depth of cut. The tolerance, however, can be changed depending on required accuracy of prediction with model.

VII. CONCLUSION

In present work, the principle of fuzzy logic is employed in combination with genetic algorithm to obtain the best combination of AWJM process parameters for machining black granite with desired depth of cut. Based on the experimental data, fuzzy model is built with the input process parameters divided into five categories and output parameter with 11 categories. This fuzzy model contains 125 fuzzy rules. By using fuzzy model, depth of cut can be predicted within 10% of deviation, for process parameters such as water jet pressure, traverse rate and abrasive flow rate. This fuzzy model is decision maker not an optimization technique. Therefore, GA in combination with fuzzy logic suggests an optimal combination of process parameters to maximize MRR while achieving desired depth. It also allows considering different objectives like cost of abrasives, cost of production, quality of surface, etc. in the selection of the best set of process parameters. For selecting the best set of process parameters considering multiple objectives, one can integrate multi-objective optimization criteria with current approach.

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