A REVIEW ON OPTIMIZATION TECHNIQUES OF ABRASIVE WATERJET MACHINING

M.Sibichakkravarthi[1], P.Uthayakumar[2], K.Vignesh[3], A. Murugarajan[4]

[1,2,3] B.E- Final year, Department of Mechanical Engineering, Sri Ramakrishna Engineering College, Coimbatore, Tamilnadu, India. E-mail Id: uthayakumar.1304240@srec.ac.in
[4] Professor, Department of Mechanical Engineering, Sri Ramakrishna Engineering College, Coimbatore, Tamilnadu, India. E-mail Id: murugarajan@srec.ac.in

---***---

Abstract - *Abrasive Water Jet Machining is an effective technology for processing various materials. This paper reviews on the various optimization techniques for process parameters of Abrasive Water Jet Machining (AWJM). In AWJM process the workpiece material is removed by impact erosion of high velocity jet of water mixed with abrasive particles. There are several optimization techniques that are used to increase the effectiveness of the AWJM process such as, Taguchi method, Response Surface Methodology (RSM), Fuzzy Logic (FL), Artificial Neural Networks (ANN) and Genetic Algorithm (GA). Based on these optimization techniques how the operating variables are changed to obtain the different optimized results is studied.*

Key Words: Abrasive Waterjet, Material Removal Rate (MRR), Kerf Geometry, Surface Roughness (SR), Stand-off distance (SoD)

1. INTRODUCTION

Waterjet cutting technology is one of the fastest growing machining processes in the world. Waterjets entered the manufacturing sector in the early 1970's for cutting soft materials like cardboard, plastics, rubber. In the mid 1980's, the abrasive water jet machining was introduced to expand the capabilities of the tool to cut hard materials like metal, ceramic, stone, glass, composite materials [1]. An abrasive waterjet is a jet of water that contains some abrasive materials such as Aluminium oxide, Silicon carbide, sodium bi carbonate, dolomite and glass beads [2] with varying grain sizes.

In this process, water goes through the thin orifice with very high pressure (about 4000-6400 bar) and enters mixing chamber with a very high velocity (nearly 4000kmph). In mixing chamber, abrasive particles along with water jet are drawn into the nozzle. Generally nozzles are made of high wear resistant materials like sapphire or diamond [3]. This mixture containing water, abrasive particles and air leaves nozzle. Having received a lot of kinetic energy and velocity by water jet, the abrasive particles cause wearing and machining when they impact on the work piece surface. Advantages of abrasive water jet cutting are the ability to cut almost all materials, no thickness limitation to cut materials, no thermal distortion, high flexibility and small cutting forces [4]. Because of these capabilities, this cutting technique is more cost-effective than traditional and some non-traditional machining processes.

It is also an environmentally friendly technique that can be adopted for processing number of engineering materials particularly difficult-to-cut materials. However, AWJM has some limitations and drawbacks. It may generate loud noise and a messy working environment. It may also create tapered edges on the kerf characteristics [5], especially when cutting at high traverse rates.

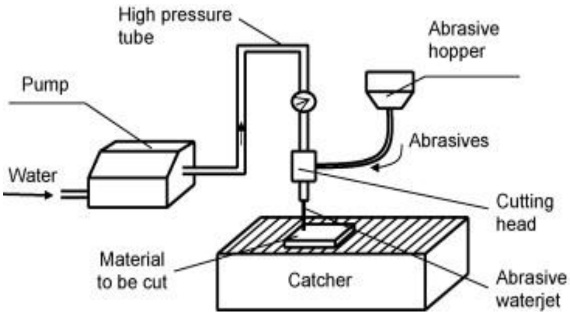

Figure-1: Abrasive waterjet machining system

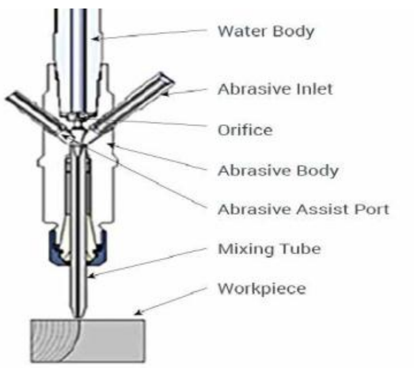

Figure-2: Principle of operation of Abrasive Waterjet

2. OPTIMIZATION

Optimization is the process methodology of making Abrasive Waterjet Machining as effective as possible. Machining is one of the most important and widely used manufacturing processes. [24] Due to complexity and uncertainty of the machining processes, soft computing techniques are being preferred to physics-based models for predicting the performance of the machining processes and optimizing them. [6]

2.1 Optimization process parameters

The AWJM is characterized by a large number of operational parameters which determine the efficiency, economy and quality of the entire process. In general, the parameters in AWJM can be divided into four categories: 1.Hydraulic parameters 2.Mixing and Acceleration parameters 3.Cutting parameters 4.Abrasive parameters [8,25]. The table-1 shows that optimization of various process parameters (usage point of view)

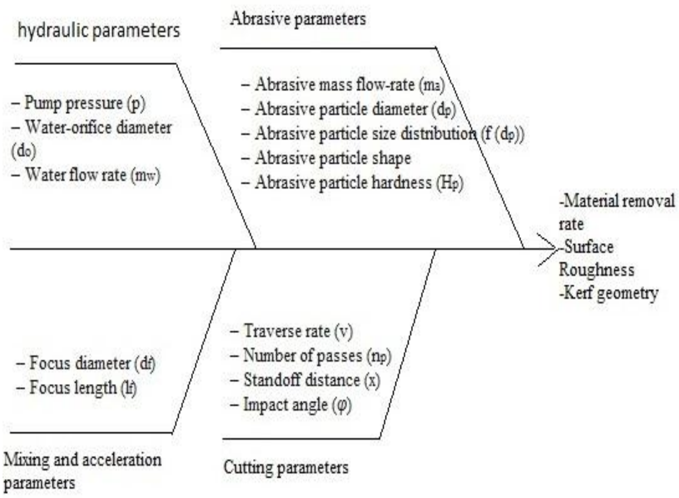

Figure-3: Optimization process parameters

2.2 Optimization Techniques

In this study, Taguchi method, Response Surface Methodology and the soft computing techniques [7] (such as, ANN, GA, Fuzzy logic) are observed.

2.2.1 Taguchi's method

Taguchi's Design of Experiments (DOE) is a simple tool that can be used in various experimental situations. The main parameters are located at different rows in a designed orthogonal array. Thus, an appropriate number of statistically important experiments are conducted. Generally the Signal to Noise ratio (η, dB) represents the response of the data observed in the Taguchi's Design of Experiments [9]. DOE techniques enable designers to determine simultaneously the individual and interactive effects of many factors that could affect the output results in any design.

Taguchi methodology designed experiments for transformation induced plasticity (TRIP) sheet steels on surface quality characteristics by Jon kechagies et al., [10]. The experiments were carried out by TRIP 700 CR-FH and TRIP 800 HR-FH. As response variables, mean kerf width and average surface roughness were selected. The experimental results were analyzed using analysis of means and analysis of variance methods in order to correlate the AWJM process parameters with the response variables. The experimental design indicated that the nozzle diameter is one of the most important parameters that affects the mean kerf width and surface roughness. The standoff distance was the second most important parameter within the experimental range tested.
The problem of waterjet coal cutting is a multi-response problem. Taguchi-Fuzzy decision method had been used to improve the productivity of coal mines by Vinay Sharma et al.,[11]. As considering the productivity, the depth of cut and kerf width play major role. From ANOVA results, it can be noticed that pressure (56.7%) and number of passes (33.8%) made the larger contributions to the depth of cut. Standoff distance made the large effect on kerf width.
The studies on the use of single mesh size garnet abrasives in abrasive waterjet machining for cutting aluminum were done by M.Kantha Babu et al.,[12]. The influence of three different single mesh size abrasives, pressure, traverse rate, and abrasive flow rate on depth of cut, top kerf width, bottom kerf width, kerf taper and surface roughness were investigated. Experiments designed using standard L9 orthogonal array. Single mesh size abrasives were found to yield decreased surface roughness than multi mesh size abrasives.
The performance optimization of abrasive waterjet technology in granite cutting was investigated through design of experiment techniques by G.Aydin et al.,[13]. It can be stated that the traverse speed, standoff distance, abrasive size and water pressure have a discernible effect on the surface roughness of the granite. The input parameters traverse speed, abrasive flow rate and abrasive size were found to be the most significant factors on the cut depth of the granite. On the other hand, it can be concluded that other machining parameters were found to be insignificant on the cut depth.

2.2.2 Response Surface Methodology

Response surface methodology (RSM) is a statistical method used to relate the input parameters with the responses or the quality characteristics. The method proceeds with the generation of a mathematical model. The generated quadratic model was used to develop the response surfaces.

The response surface methodology (RSM) design has been used to develop the empirical models for response characteristics by Adalarasan Ramalingam et al.,[14]. The material selected in this study was high speed steel of M2 grade. A higher jet transverse rate was observed to spoil the surface finish while a lower value of Standoff distance was found to produce effective cut surface with better surface

	Response parameters	Process parameters	References
Optimization of	Surface roughness	Pressure, traverse rate, abrasive flow rate	M.Kantha Babu & O.V.Krishnaiah Chetty[2]
		Water pressure, traverse rate, SoD	M.Sreenivasa Rao et al.,[9]
		Material thickness, Nozzle diameter, SoD, Traverse speed	John Kechagies et al.,[10]
		Single mesh abrasive size	M.Kantha Babu & O.V.Krishnaiah Chetty[12]
		Traverse speed, SoD,	G.Aydin, I. Karakurt, K.Aydiner [14]
		Abrasive mass flow rate, nozzle speed, Traverse speed, SoD, Pressure within the pumping system, Abrasive mass flow rate, nozzle speed	Jagadish et al.,[18]
		Traverse speed, waterjet pressure, SoD, Abrasive grit size, Abrasive flow rate	Azlan Mohd Zain et al.,[22]
		Pump pressure, nozzle feed rate, SoD	Fuat Kartal [25]
	Material removal rate (MRR)	Water pressure, jet feed speed, abrasive mass flow rate	Zhongbo yue et al.,[15]
		Water pressure, diameter of nozzle, traverse rate ,mass flow rate of water, mass flow of abrasives	Neelesh K. Jain, Jain, Kalyanmoy Deb [21]
		Pump pressure, Abrasive flow rate	Fuat kortal [25]
	Kerf Width	Recharging of abrasive particles	M.Kantha Babu & O.V.Krishnaiah Chetty[2]
		Traverse speed, water pressure	J.Wang[5]
		Nozzle diameter, Sod, material thickness	John Kechagies et al.,[10]
		Waterjet pressure, traverse rate, SoD, Number of passes	Vinay sharma et al.,[11]
		Single mesh size abrasives	M.Kantha Babu & O.V.KrishnaiahChetty[12]
	Kerf angle	Traverse speed, SoD, abrasive flow rate	Gokhan Aydin et al.,[16]
	Depth of cut	Abrasive particle size, recharging abrasive particles	M.Kantha Babu & O.V.Krishnaiah Chetty[2]
		Water pressure, abrasive flow rate, traverse speed, SoD	Ushasta Aich et al.,[3]
		Traverse speed, water pressure	J.wang[5]
		Abrasive mass flow rate, focus diameter, traverse rate, pump pressure	Pratik.J[8]
		Waterjet pressure, traverse rate, SoD, Number of passes	Vinay sharma et al.,[11]
		Traverse rate, abrasive flow rate, abrasive size	G.Aydin, I. Karakurt, K.Aydiner [14]
		Water pressure, abrasive flow rate, jet transverse rate	D. S. Srinivasu, N. Ramesh Babu [7]

Table-1 : Optimization of process parameters (usage point of view) characteristics. A higher flow rate of fine abrasives could produce better surfaces as well.

An experimental investigation using RSM was carried out to explore the influence of process parameters (Including water pressure, jet feed speed, abrasive mass flow rate and jet impact angle) on the MRR in the radial-mode AWJ turning process by Zhongbo yue et al.,[15] when turning alumina ceramic. MRR increased with an increase in the water pressure P. They stated that a higher water pressure increases the velocity of abrasive particles and their kinetic energy as well and further increases the depth of turning and material removal rate. At relatively large water pressure or surface speed, an increase in abrasive mass flow rate is associated with a steady increase of the MRR while the increase rate decreases with the abrasive mass flow rate. But at relatively low water pressure or surface speed, the MRR first appeared to be increasing and then decreasing with the increase of abrasive mass flow rate. Hence, for a given pressure or surface speed, there should be an optimum abrasive mass flow rate to achieve the maximum MRR. If the exposure time increases, more abrasive particles participate in erosion and thus increase the depth of penetration and the MRR. Therefore, a low feed speed is always suggested to get high MRR. It was observed that the Material Removal Rate increased with the nozzle titled angle and shows maximum value at near 90°.

2.2.3 Neural Networks

Neural networks are systems that can acquire, store and utilize knowledge gained from experience. An artificial neural network is capable of learning from an experimental data set to describe the nonlinear and interaction effects with great success.[6,23] It consists of an input layer used to present data to the network, output layer to produce ANN's response, and one or more hidden layers in between. The input and output layers are exposed to the environment and hidden layers do not have any contact with the environment. ANNs are characterized by their topology, weight vectors, and activation function that are used in hidden and output layers of the network. A neural network is trained with a number of data and tested with other set of data to arrive at an optimum topology and weights. Once trained, the neural networks can be used for prediction.

Neural Networks approach has been proposed to reduce the complexity of the process parameter estimation by Pratik. J et al.,[8]. Two neural network approaches, back propagation (BBN) and radial basis function (RBFN) networks were proposed. These paradigms were selected because of their successes in function approximation problems in the literature and their universal approximation properties. The BPN is a supervised learning algorithm. It uses the input-output data to train the internal weights via an iterative process. The weights are adjusted using gradient descent to minimize the error on the network outputs. The sigmoid function is typically used as an activation function for the neurons in a BPN.

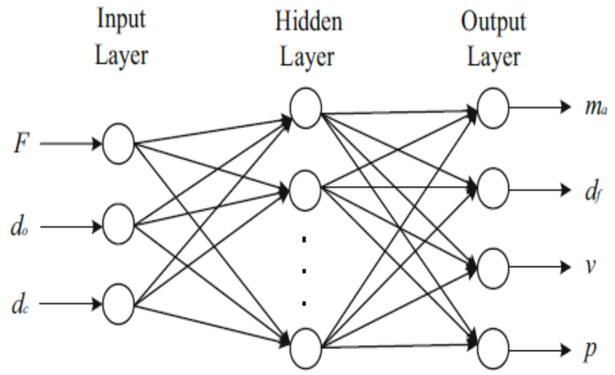

Figure- 4: Neural Network strategy

The training process of a RBFN begins with an unsupervised clustering phase followed by a supervised learning phase using a gradient descent approach. The RBFN performs curve fitting to the input-output data in a high dimensional space. The RBFN is a two-layer network. i.e., a network that has two layers of weights. The RBFN typically employs the Gaussian kernel function at the hidden layer. The results of both networks were compared with two systems of regression models. The results showed that the RBFN trained with focused training can model the AWJM relationship more accurately than the BPN and the regression models.

Multi-Layer Perception (MLP) type of ANNs was used for prediction of Kerf Angle by Gokhan Aydin et al.,[16]. MLP is the most widely used ANNs type for prediction. Training is a very important procedure for a MLP to accomplish a required task. Training of MLP means to determine the best weights of connections between the neurons in order to obtain minimum difference between actual and predicted value of dependent variable. In a prediction problem, the number of input neurons is equal to the number of independent variables and the output neurons are equal to the number of the dependent variables. It was concluded that the Kerf Angle of the tested rock increased with an increase in standoff distance, transverse speed and abrasive flow rate.

A full factorial experimentations were carried out in order to feed the data into the Neural Network system by D.S.Srinivasu et al.,[17]. The collected data was used to develop the ANN model for predicting the depth of cut with known parameters such as, water pressure, abrasive flow rate, jet transverse speed and the diameter of the focusing nozzle. For the development of the ANN model the total experimental data were divided into training, validation and testing data sets. From the experimental data, 70% was selected for training, 10% for validation and remaining 20% for testing the developed model. The Back Propagation method was used for training the network.

2.2.4 Fuzzy logic

The fuzzy logic is one of the most widely tools for modeling of human reasoning to reduce the uncertainties in the system.[6] The FL uses the linguistic terms to develop relationship between the input-output variables. The fuzzy interference system consists of 1.Fuzzification 2.Knowledge base (rule evaluation) 3.Interference from the knowledge base (aggregation) 4.Defuzzification.

Prediction of surface roughness quality of green abrasive water jet machining by Jagadish et al.,[18] with process parameters abrasive material grain size, stand-off distance, abrasive mass flow rate, nozzle speed and pressure within the pumping system. Taguchi method was used to development of the database. Fuzzy set values defines the degree of membership of an object in a fuzzy set. Till date there has been no standard method of choosing the appropriate contour of the membership functions for the fuzzy sets of control parameters. Based on the trial and error methods, this paper used Gaussian type of membership functions for representation of fuzzy sets. Formulation of fuzzy rules was carried out using MATLAB toolbox. Final step is defuzzification, in which a crisp value was extracted from a fuzzy set as a representative value.

Fuzzy Axiomatic Decision method was used by Anant V. Khandekar et al.,[19]. Fuzzy Axiomatic Decision methodology is a strong scientific and logic foundation. As a decision making tool, Fuzzy Axiomatic Design principles can be applied in a variety of fields of manufacturing engineering and also for other non-engineering applications. But this is a graphical approach and hence demands for manual interpretation at intermediate steps. But, it is a time consuming process.

The fuzzy set-based techniques were used to predict by M.Chandrasekaran et al.,[6] . It can be quite effective in converting subjective knowledge/opinion of the skilled operator into a mathematical framework. The feed values more than the upper threshold value assigned as membership grade 1 and lower than a lower threshold value assigned a membership grade 0. Thus the fuzzy set theory is a tool for computing with language. The fuzzy set-based prediction system takes input data and carries out "fuzzification". In the fuzzification process, the input data undergo some translation in the form of linguistic terms such as "low feed", "average cutting speed", "high depth of cut", "very high cutting force", etc. The translated data are sent to an inference engine, which applies a set of predefined IF-THEN rules. The output of inference system in linguistic form will go through defuzzification process, which converts it to numerical data.

For multiple response problems it is important that we need to optimize them simultaneously rather than optimizing one response at a time, investigated by Vinay Sharma et al.,[11]. In this study, it was decided to analyze the case using signal–noise ratio (SNR) and fuzzy rule based inference. Fuzzy rules were derived from the knowledge and experience.
FL have potentially used in the prediction of machining performance in milling and abrasive water jet machining process. It is because, machining performance like depth of cut and surface roughness for both machining process needs to be investigated more by M. R. H Mohd Adnan et al.,[20]. Since there are very significance in industrial needs in order to obtain desired product. The fuzzifier can transform crisp or fuzzy set data into suitable linguistic values by the definition of linguistic variables the types of membership function (MF), such as Triangular, Trapezoidal, Gaussian or Bell MFs. The MF will map each element of the input variables into a membership grade between 0 and 1. In FL, rules and membership functions need to be determined by experts and they could not be determined and adjusted automatically.

2.2.5 Genetic Algorithm

GA is the process of natural evolution by incorporating the "survival of the fittest" philosophy. In GA, a point in search space is represented by binary or decimal numbers, known as string or chromosome. Each chromosome is assigned a fitness value that indicates how closely it satisfies the desired output. A group of chromosomes is called population. A population is operated by three fundamental operations, 1.Reproduction (to replace the population with large number of good strings having high fitness values), 2.Crossover (for producing new chromosomes by combining the various pairs of chromosomes in the population) and 3.Mutation (for slight random modification of chromosomes). A sequence of these operations constitute one generation. [6] The process repeats till the system converges to the required accuracy after many generations. The genetic algorithms have been found as a very powerful tool in optimization.

Operation of GA begins with generation of a set of random solutions (known as population). Each solution is evaluated to find its fitness value. Higher fitness value indicates goodness of the solution. The generated population is then operated by the reproduction, crossover and mutation operators to create the new population which is evaluated and tested for the termination criterion. MRR in AWJM increases with water jet pressure at nozzle exit and so as the power consumption. Therefore, value of the water jet pressure corresponding to the limiting power consumption value will be its optimum. MRR was found to increase with diameter of abrasive-water jet nozzle and feed rate of nozzle initially very rapidly but after a certain value it became more or less steady, while power consumption is independent of these parameters investigated by Neelesh K. Jain et al.,[21]. GA can be either binary or real-coded. Binary-coded GA discretizes the search space and accuracy of the optimum solution depends on the string length of the decision variables, therefore real coded GA with various parameters was used.

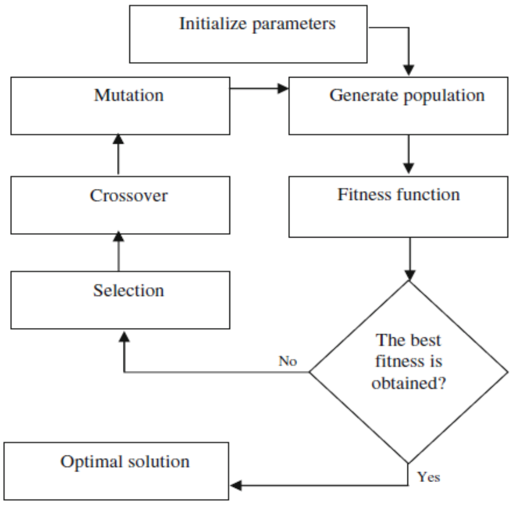

Figure-5 Genetic Algorithm flow chart

Optimization using GA process leads to the minimum value of Ra by Azlan Mohd Zain et al.,[22] . The GA repeatedly modifies a population of individual solutions. At each step, the GA selected individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population evolved toward an optimal solution. In the GA-based optimization module, the predicted equation of the Regression model in Regression modeling module would become the objective function for an optimization solution. The minimum and maximum coded value for process parameters of the experimental design would define the boundary for optimization solution. Based on some of the criteria, the minimum predicted performance value at the optimal process parameters was estimated.

3. CONCLUSIONS

In this paper, various optimization techniques of the Abrasive Waterjet Machining parameters to get effective response have been studied.

- Researchers studied the AWJM process on different materials and concluded different remarks on abrasive workpiece interaction. Due to potential advantages, AWJM process is now preferred in various industrial sectors for production of various complicated parts.
- Taguchi method of experimental design is widely used for producing high quality products at low cost. ANOVA is required for estimating the error variance for the factors effects and also variance of the prediction error. Increasing the
- In RSM, a mathematical model has been developed and used to develop the response surfaces. (also Design Expert software was used to generate the mathematical model)
- Neural Network method implies 'learning from the past experience'. In this method, 1.Multilayer perceptron (MLP) is a feed forward neural network with one or more hidden layers.2.RBFN-Radial basis function consisting of a single hidden layer with nonlinear processing neurons.3.BPN-Back propagation method is an iterative supervised algorithm
- Fuzzy logic is working based on knowledge and experience. If-then rules are used to optimize the input parameters. And it is also used in hybrid systems.
- GA is the powerful optimization tool than compared to the other optimization techniques discussed previously. In AWJM process, MRR and Ra have been optimized through an iterative process based on GA.

Though there are several optimization techniques, the hybrid optimization technique (combination of two optimization techniques such as Neuro-genetic approach, Neuro-fuzzy approach, integrated approach of ANN and SA) found to be more efficient.

REFERENCES

[1] M.M. Korat, Dr. G.D. Acharya (2014) "A Review on current research and development in Abrasive Waterjet Machining" Int. Journal of Engineering Research and Applications ISSN: 2248-9622,Vol 4 pp.423-432

[2] M. Kantha Babu and O. V. Krishnaiah Chetty (2002) "Studies on Recharging of Abrasives in Abrasive Water Jet Machining" Int J Adv Manuf Technol 19:697–703

[3] Ushasta Aicha, Simul Banerjeea, Asish Bandyopadhyaya, Probal Kumar Das (2014) "Abrasive Water Jet Cutting of Borosilicate Glass" Procedia Materials Science 6 775 – 785

[4] Daniel Krajcarz (2014) "Comparison Metal Water Jet Cutting with Laser and Plasma Cutting" Procedia Engineering 69 838 – 843

[5] J. Wang (1999) Abrasive Waterjet Machining of Polymer Matrix Composites –Cutting Performance, Erosive Process and Predictive Models Int J Adv Manuf Technol 15:757–768

[6] M.Chandrasekar, M.Muralidhar, C.Muralikrishna U.S Dixit (2010) "Application of soft computing techniques in machining performance prediction and optimization: a review" Inter journal of Adv Manufacturing technol 46:445-464

[7] R. Venkata Rao & V. D. Kalyankar (2014) "Optimization of modern machining processes using advanced optimization techniques: a review" Int J Adv Manuf Technol 73:1159–1188

[8] Pratik J, Parikh, Sarah S. Lam (2009) "Parameter estimation for abrasive waterjet machining process using neural networks" Int J Adv Manuf Technol 40:497–502

[9] M.Sreenivasa Rao, S.Ravindar, A.Seshu kumar (2014) "Parametric optimization of Abrasive Waterjet Machining for Mild steel: Taguchi approach" International journal of current Engineering and Technology P-ISSN 2347-5161

[10] John kechagies, George Petropoulos, Nikolaos Vaxevanidis (2012) "Application of Taguchi design for quality characterization of abrasive waterjet machining

of TRIP sheet steels" Inter journal of Adv Manufacturing technol 62:635-643

[11] Vinay sharma, Somath chattopadhyaya, Sergej Hloch (2011) "Multi response optimization of process parameters based on Taguchi-Fuzzy model for coal cutting by waterjet technology" Inter journal of Adv Manufacturing technol 56:1019-1025

[12] M.Kantha Babu, O.V Krishnaiah Chetty (2006) "A study on the use of Single mesh size abrasives in abrasive waterjet machining" Inter journal of Adv Manufacturing technol 29: 532-540

[13] G.Aydin, I.Karakurt, K.Aydiner (2011) WJTA-IMCA conference and Expo, Houston, Texas

[14] Adalarasan Ramalingam, Santhanakumar (2016) "Application of Response Surface Methodology in Abrasive Waterjet Machining of high speed steel" International Journal of Applied Engineering Research ISSN 0973-4562 Vol.10 No.33

[15] Zhongbo Yue, Chuanzhen Huang, Hongtao Zhu, Jun Wang, Peng Yao, ZengWen Liu (2014) 71:2107-2114 "Optimization of machining parameters in the abrasive waterjet turning of alumina ceramic based on the response surface methodology" Int J Adv Manuf Technology 71:2107–2114

[16] Gokhan Aydin, Izzet Karakurt, Coskum Hamazacebi (2014) "Artificial neural network and regression models for performance prediction of abrasive waterjet in rock cutting" Int J Adv Manuf Technol 75:1321–1330

[17] D. S. Srinivasu, N. Ramesh Babu (2008) "An adaptive control strategy for the abrasive waterjet cutting process with the integration of vision-based monitoring and a neuro-genetic control strategy" Int J Adv Manuf Technol 38:514–523

[18] Jagadish, Sumit Bhowmik, Amitava Ray (2015) "Prediction of surface roughness quality of green abrasive water jet machining: a soft computing approach" J Intell Manuf DOI 10.1007/s10845-015-1169-7

[19] Anant V. Khandekar, Shankar Chakraborty (2016) "Application of fuzzy axiomatic design principles for selection of non-traditional machining processes" Int J Adv Manuf Technol 83:529–543

[20] M. R. H. Mohd Adnan, Arezoo Sarkheyli, Azlan Mohd Zain, Habibollah Haron (2015) Artif Intell Rev 43:345–379

[21] Neelesh K. Jain, V.K. Jain, Kalyanmoy Deb (2007) "Optimization of process parameters of mechanical type advanced machining processes using genetic algorithms" International Journal of Machine Tools & Manufacture 47 900–919

[22] Azlan Mohd Zain, Habibollah Haron, Safian Sharif (2011) "Genetic Algorithm and Simulated Annealing to estimate optimal process parameters of the abrasive waterjet machining" Engineering with Computers 27:251–259

[23] H. Sevil Ergur · Yusuf Oysal (2015) "Estimation of cutting speed in abrasive water jet using an adaptive wavelet neural network" J Intell Manuf 26:403–413

[24] Adnan Akkurt, Mustafa Kemal kulekci, Ulvi Sekar, Fevzi Ercan (2004) "Effect of feed rate on surface roughness in abrasive waterjet cutting applications" Journal of Materials Processing Technology 147 389-396

[25] Fuat Kartal (2016) "A review of the current state of abrasive waterjet turning machining method" Inter journal of Adv Manufacturing technol