APPLICATION OF ANN FOR PREDICTING MACHINING CHARACTERISTICS

Abstract

Enhancement in the quality of a product is the key objective of all the processes. In order to control a process, the parametric behavior of the same should be accountable. The experimental studies help explore variables involved and their effect on responses, but applying advanced computational techniques using ANN is becoming an alternate tool. The advent of ANN in reducing experimentation time and materials as well as its emergence as a very effective prediction tool is discussed in this chapter.

Keywords: ANN, Prediction, Process simulation, AWJM, EDM, LBM, Activation function, Feed forward back propagation, Multilayer Perceptron, MRR, Surface roughness

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I. INTRODUCTION

The common objective of all the Manufacturing Industries is to develop a product of highest quality within a stipulated time with minimum or zero material wastage. A material undergoes several kinds of processes or treatments before it is released as a final product.

The controlled process parameters and the material interactions determine the effectiveness of the machining processes and experimental findings are the only means for the comprehensive study of these material-machine interactions which is possible only at the expense of both material and time; But limited set of experimental trials fails to correlate the process parameters with the machining characteristics likewise machining processes which are expensive and time consuming also requires an alternative.

The combination of software technology and basic theories allows the emergence of "intelligent" agents like ANN which is capable of dealing with subjective data and can make decision based on the analysis of relationship between the available dataset.

ANN is valid as an adaptive processing system since it can update its internal structure to meet the objective of the function that has been built previously enabling the user to modify or include new set of data into it by learning continuously and instantaneously upgrading the results within the process elements. This is the most advantageous features that attract Medical, Chemical, Metallurgy, Machining and other engineering fields to implement the ANN technique posing it as a universal tool.

Modern machining processes which are intended to produce high precision parts involve the active contribution of each and every parameter of the process. Therefore it becomes tedious to develop a mathematical model using conventional and other computational techniques that requires long dedicated time period for analyzing complex systems.

The recent R&D works related to Machining Processes involves the adoption of Artificial intelligence. Excessive number of such studies has declared the application of ANN being the most reliable technique for optimization and prediction of machining characteristics.

For example the construction of mathematical model of Abrasive Water Jet Machining of newer materials like MMCs, PMCs etc. that offer varying material properties along different directions needs extensive knowledge on several parametric behaviors such as Hydraulic (a.water Jet Pressure b.Water Orifice Dia), Abrasive parameters (particle shape, diameter, hardness, mass flow rate), Cutting parameters (SOD, Jet Impingement Angle, travers rate, number of passes) and Mixing parameters (based on nozzle and diameter). One can think of applying the ANN tool to find out the optimized parameters for the required characteristic responses in such cases where the complexity increases.

II. COMPARISON WITH OTHER COMPUTATIONAL TOOLS FOR PREDICTING AND ANN POTENTIAL FOR PROCESS SIMULATION

The simulations of machining processes have also been done with the help of other models. The simulation of powder bed fusion process to evaluate the formation of grains has been done using CFD and phase field model combination taking into account the basic process parameters like LASER power and speed of scan. [1]

A mathematical model can also be employed to study the relationship between the stress distribution and 3D printing parameters. [2]

FEA models like 3D FE model is another technique that is able to examine the factors like dimension of melting pool and profile of the deposited layer in a fused deposition printing process.[3][4]

ABAQUS tool is also capable of building an effective model for simulating the deformation process of number of predefined structures. [5]

Prediction studies made on Wire EDM process has concluded that ANN has outperformed the response surface predictive models by expressing more accurate results based on RMS error metrics and determination coefficient. [6]

All these studies show the involvement of limited number of features depending on the variation of simulation from micro scale to macro scale. This inhibits the deeper insight into a process. Also it is not feasible to forecast the complex modern machining processes effectively within a confined timeline.

The adoption of Machine learning which consists of Data driven models like ANN can give the in depth understanding of the machining processes. The potential advantage is it eliminates the development of various multi-physics equations. Instead the model learns the correlation for inputs and outputs automatically depending on the data available for training.

A study on prediction of stresses in struts and joints has revealed that the ANN is capable of doing the job in a fraction of second wherein FE simulations took more than five hours for the same study. [7]. Another study mentioned the ANN being 250 times quicker in predicting material properties compared to the FE simulations.

ANN with different kinds of techniques to handle a limited amount of data for training with which it is able to build a model of greater accuracy furthermore it is capable of manipulating incomplete information and produces an optimal solution. These key features allow the application of ANN in process monitoring for quality, design, part orientation etc.

III. APPLICATION OF DIFFERENT ANN TOPOLOGIES

ANN with different topologies are applied for predicting the processes, the network structure with varied number of neurons in all the three layers (input/hidden/output) have the impact on the accuracy. This also varies with the combination with the activation functions used like Sigmoid, Tanh etc. thus depending on the objective of the study types of algorithm are applied.

From the studies on the application of ANN based on the number of neurons variations in each layer it is evident that the increase in number of neurons in Input layer has resulted in noticeable improvement in the accuracy, similarly the increase in number of neurons on hidden layer has shown the same effect resulting in lower error on the other hand decrease in number of neurons has also resulted in less error and increased number of neurons in output layer has the same impact on the accuracy. All these studies conclude that the optimal number of neurons selection is a critical factor. The studies suggest the adoption of neurons based on the application, input variables listed, output responses expected in combination with activation function employed.

Further the network types also decides effectiveness of ANN application; these network types are decided based on the objective , feasibility to integrate with other algorithm for achieving better accuracy. For example the integration of Genetic Algorithm with simple back Propagation network.

Other networks like Feed forward Back propagation is most commonly employed type for prediction studies of machining processes. Radial Basic function network, multilayer Perceptron neural network, Convolution Artificial Neural Networks etc. are also marked their efficiency in the process modeling, image processing etc. [8]

IV. APPLICATION OF ANN AS PREDICTION TOOL IN MACHINING PROCESSES

Several research works established on the artificial neural network (ANN) approach are successful in reaching the objectives satisfactorily. Most of the studies that rely on ANN for prediction and optimization involved the modern machining and manufacturing processes. Application of ANN in such areas is discussed in this section.

R. A. Kapgate et al. [9] have modeled the complex process of wire electrical discharge machining with the help of ANN. The study involves the machining of aluminium silicon carbide metal matrix composite. 432 experimental trial data were used for training and building the correlation. The ANN was set up using visual Basics platform. The network structure implemented for the prediction and optimization of the data was 5-4-1 with one hidden layer. Eleven process parameters were taken for the mathematical modeling of the process which were reduced to 5 vital dimensionless numbers through dimensional analysis.

The ANN with univariate analysis was capable of deciding the range of influencing length of respective process parameters. The ANN employed here was also efficient in evaluating the optimum parameter set for maximizing MRR, finer surface finish along with minimal electric kerf, that was helpful in guiding the manufacturers to improve productivity by varying the required process parameters.

S. B. Prajapati et al. [10] have also employed the ANN to predict the process parameters in their study on machining of AlSi A2 using Wire EDM. The experiments were designed through Taguchi technique. Pulse ON and off time, voltage , wire tension and feed were taken as input parameters to predict the MRR, Gap current, kerf and surface roughness. The experimental trials were fed to train, test and validate the data for prediction. Study stated ANN as an effective prediction tool with very close agreement of estimated data with very less error. The ANN topology used is as shown in figure 1.

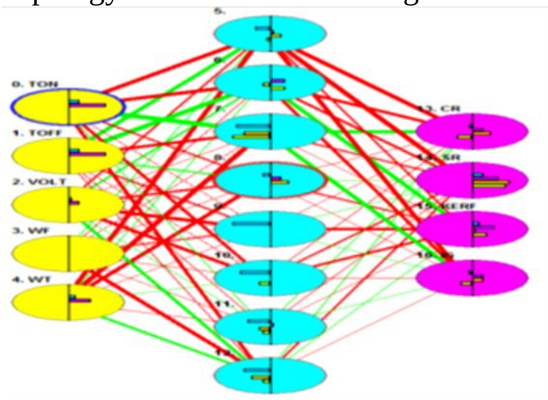

Figure 1: [10]

Mangesh et al. in their study on Wire EDM machining using CNC for processing of Al2124SiCp composites described the relative stability of the ANN in estimating the responses with Dimensional Analysis. The work considered the coefficient of thermal expansion and thermal conductivity of the specimen along with other four process parameters. The network topology used was Levenberg-Marquardt back propagation with hidden layer consisted of 15-20 number of neurons. The analysis utilized the 70% of the experimental trials for training and15% of the trials was fed to testing and validating phase each. Estimation of surface roughness and MRR through DA alone and ANN independently was done. The results and the discussions with the help of correlation coefficients clearly support the ANN meeting the greater accuracy than Dimensional Analysis as shown in the figure 2 and 3. [11] And can be reliable for industrial applications. The basic structure of ANN employed for the prediction study is shown in the figure 4.

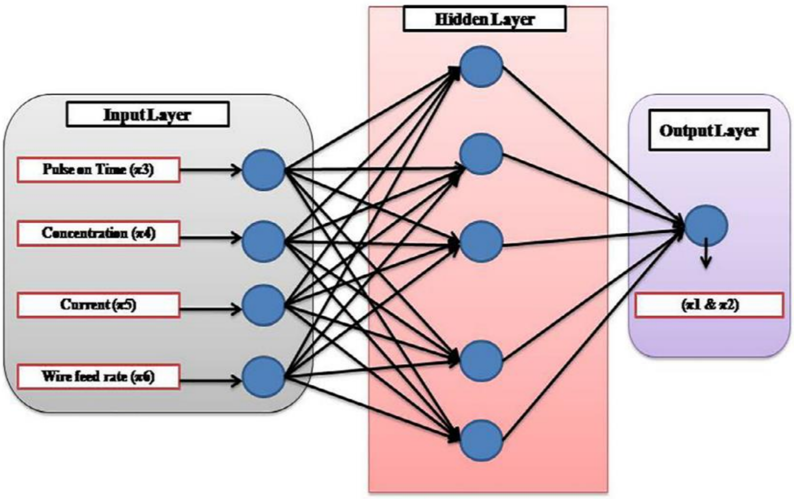

Figure 4: ANN architecture [11]

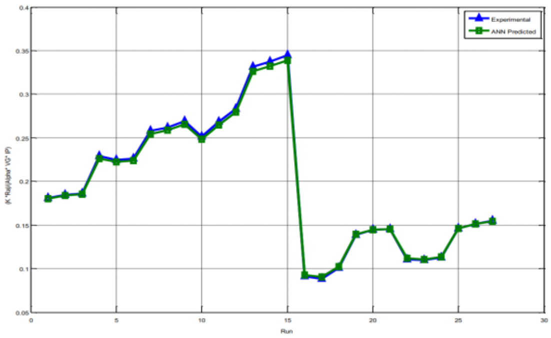

Figure 2: ANN with experimental data [11]

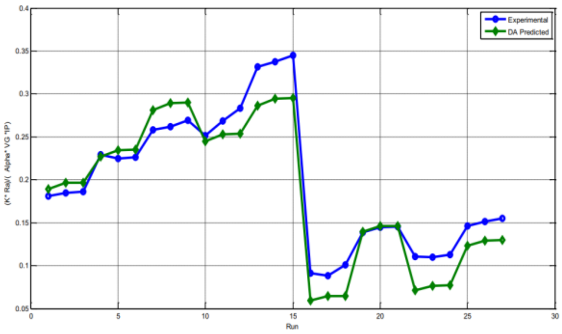

Figure 3: DA with experimental data[11]

K. S. Jai Aultrin et al.[12] in their prediction study on Abrasive water jet machining of Lead-Tin alloy have applied Feed forward Back propagation algorithm. The network was trained with 36 experimental data out of 46 trials of machining. Five process parameters like water pressure, orifice diameter etc. were used as inputs. ANN through MATLAB with 20 hidden layers was considered for the analysis with the Sigmoid activation function. The study summarized the ANN as a heuristic model that successfully could predict the Material removal rate and surface roughness with very little deviation from the experimental outputs.

Y. M. Elattar et al. [13] have made an attempt to machine ARMOX shielding steel, a military applications material plate by AWJM process and process control through ANN. The network architecture of type feed forward BP consisted of 4-10-2 neurons combination. The prediction of MRR and surface roughness was based on the four control variables. The work reconfirms the ANN as the better tool for prediction due to the regression plots showing the best agreement in all the three phases of training, testing and validating as in the figure 5.

They have also analyzed for the optimum number of neurons for achieving less error of estimation that can be evident from figure 6 showing the minimum error at when the neurons is taken as10. The study also highlights the optimum number of training cycles that is responsible for the accurate predictions based on mean square error refer figure 7.

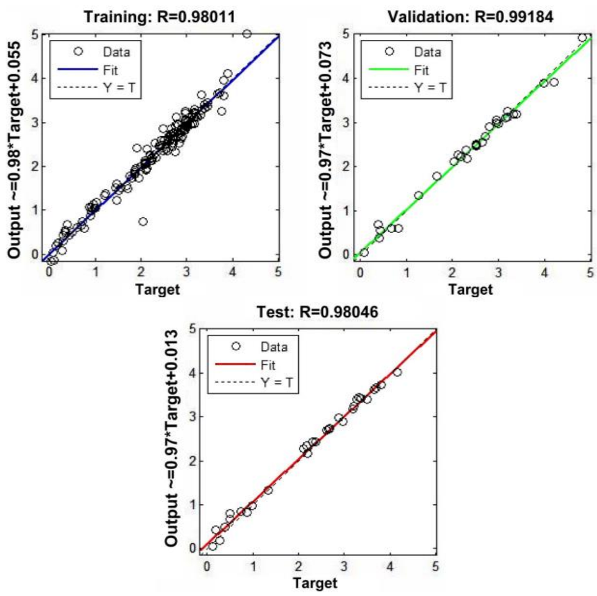

Figure 5: [13]

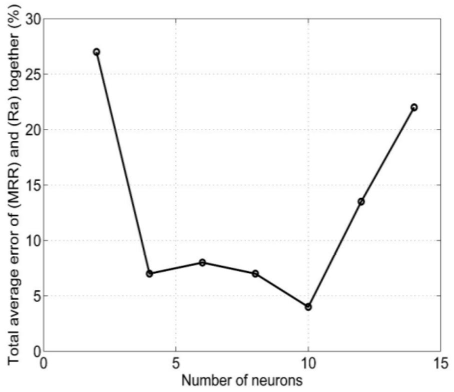

Figure 6: [13]

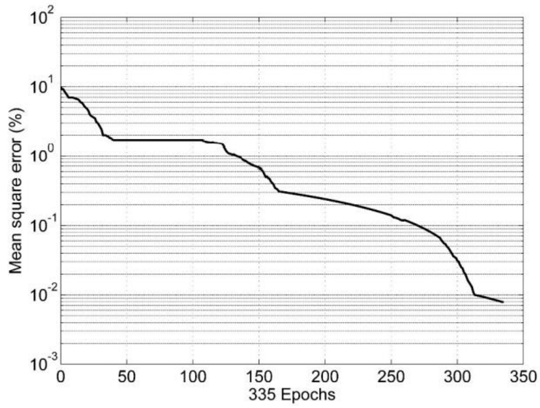

Figure 7: [13]

Mirko Ficko et al. in their investigation on machining of stainless steel through Abrasive Water Jet Machining have applied the ANN to explore the capabilities of the feed-forward topology in predicting the surface roughness for three controlled variables of the process as Mass flow rate of abrasives, depth of cut and traverse speed. The analysis was able to achieve the minimum error. The ANN predicted values of surface roughness were compared with experimental trials. Improved prediction results were obtained upon modifying the input factors of the machining enabling the model proposed in the study to work as an effective optimization tool eliminating the experimental time and material cost. [14]

The overall success of business in the manufacturing industries is decided by the quality of the products; quality is primarily dictated by the tool property. In this regard P.J.Bagga et al. have carried out a research to estimate the tool wear behavior through ANN model projecting it as a condition monitoring method. This study is an example for application of ANN in controlling the tool wear through the evaluation of cutting force and vibration under dry turning condition. Cemented carbide tool wear on machining the medium carbon steel workpiece at varied parameters like feed, speed and DOC is recorded during nine trials that were designed using Taguchi's L_9 array. The prediction study has been validated by comparing with the direct manual measured tool wear values that has concluded the very less error resulting in very close fit. [15]

A similar type of study has been carried out by Hanief et al. wherein the researchers try to explore the effect of cutting parameters on tool life with respect to cutting forces. The forces were evaluated at varied speed, depth of cut also the feed rate. Turning of Red brass material by a HSS tool trials were built based on Full factorial design method due its reliability enhancement. They have compared the ANN prediction with Regression analysis and found that the application of ANN is preferred as the results are best fit with the experimental values as can be observed from the figures 8 and 9 [16]

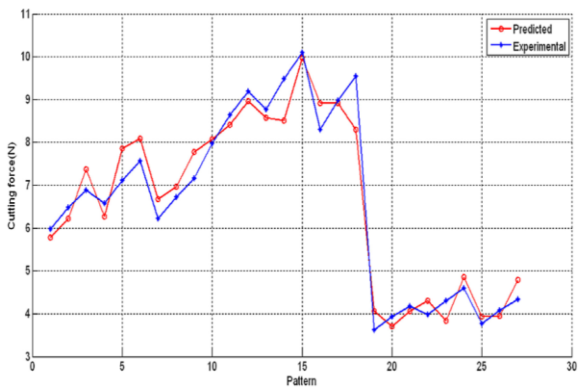

Figure 8: [16]

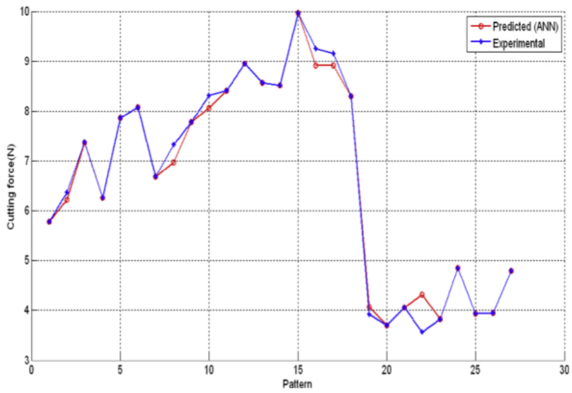

Figure 9: [16]

CNC assisted Milling of Al6061 material was investigated by R. Sanjeevi et al. for evaluating the roughness of the milled surfaces. Vision based ANN is employed to estimate the surface roughness and validated the results by practical measured with the help of stylus probe that shows the better agreement as shown in figure 10.

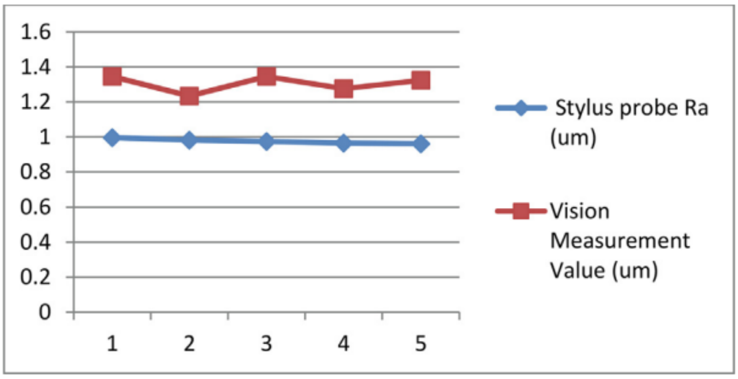

Figure 10: [17]

The study concludes the application of ANN tool as a replacement of sampling process for mass production thereby minimizing the scrap produced. [17]

The application of ANN in forming processes is a state of art; in an investigation done by Sherwan Mohammed Najm and Imre Paniti on forming of sheet metal AlMn1Mg1 have discussed the forming tool roughness impact on surface roughness of the formed product. The ANN model was fed with 108 experimental sets with an objective of predicting the average roughness and ten-point roughness values of the formed product by controlling the tool features like shape, end radius, material along with the tool surface roughness R_a and R_z. The ANN model used consisted of 5-10-2 and 5-10-1 topology of back propagation type two structures for two different tool shapes to check the impact of shape on roughness as shown in figure 11 and 12. There are six different transfer functions utilized in the network analysis like tan-sigmoid, soft max, log-sigmoid etc and at the output Purelin function is used.

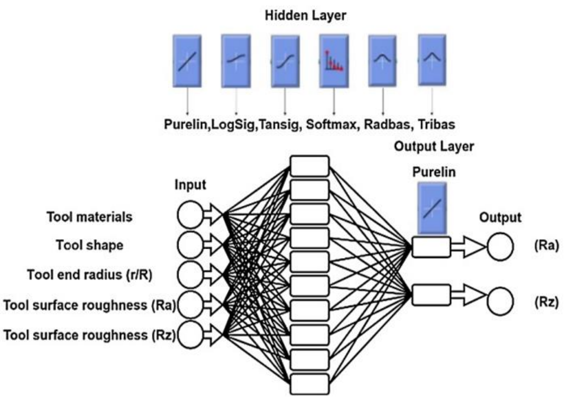

Figure 11: [18]

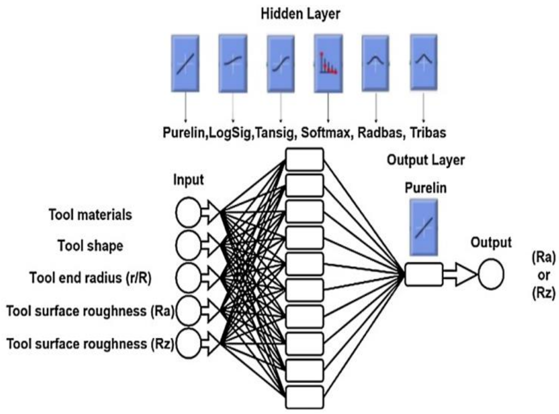

Figure 12: [18]

In this study they have reported the optimum values for surface roughness was obtained on allocating the 80% of the dataset for training and 20% for testing which proves the effect of division of data on prediction accuracy. The comparison study of ANN prediction and Support vector regression exclusively identified the effectiveness of ANN as a prediction tool with one output structure. The transfer function log sigmoid and softmax are showing the better results than other TFs. The study also list some limitations like forming conditions and size of sample etc., the study concluded the significance of tool geometry on the surface roughness of sheet. Figures 13 shows the close fitting of predicted data with experimental can be referred. [18]

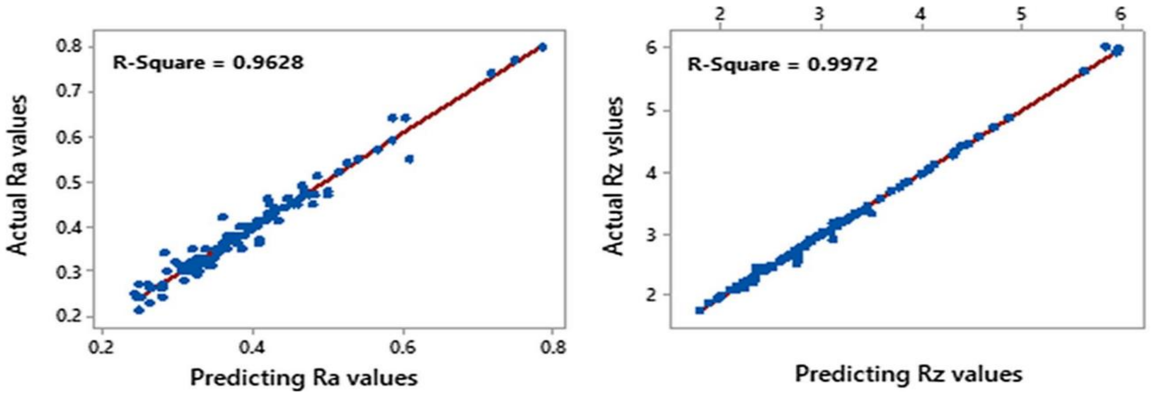

Figure 13: [18]

V. CONCLUSION

These observations from several works reconfirm the application of ANN as an efficient and successful prediction tool. The limitations of NN implementations can be discussed as follows: The effectiveness of an ANN model is driven by amount and type of data available for training. The process of collection and organization of training dataset required costs time and expensive. This necessitates the determination of set of significant parameters to train ANN also to prevent the over- or under fitting of predictions. [18]

Whereas the accuracy of the ANN when compared to other method for simulation of the manufacturing process or machining responses predictions are acceptable and thus recommends the adoption of ANN for the purpose. Therefore it is gaining its popularity in all the technological areas with its versatile evolutionary features for quick, easy and error free estimations just by the vision method without actually requiring the related dataset to be provided.

REFERENCES

[1] Acharya, R.; Sharon, J.A.; Staroselsky, A. Prediction of microstructure in laser powder bed fusion process. Acta Mater. 2017, 124, 360–371.

[2] Fergani, O.; Berto, F.; Welo, T.; Liang, S.Y. Analytical modelling of residual stress in additive manufacturing. Fatigue Fract. Eng. Mater. Struct. 2017, 40, 971–978

[3] Chen, Q.; Guillemot, G.; Gandin, C.A.; Bellet, M. Three-dimensional finite element thermomechanical modeling of additive manufacturing by selective laser melting for ceramic materials. Addit. Manuf. 2017, 16, 124–137

[4] Zhang, Y.; Chou, Y.K. Three-dimensional finite element analysis simulations of the fused deposition modelling process. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. 2006, 220, 1663–1671.

[5] Wang, Y.; Li, X. An accurate finite element approach for programming 4D-printed self-morphing structures produced by fused deposition modeling. Mech. Mater. 2020, 151, 103628

[6] Aysun Sagbas, Filiz Gürtuna and Ulviye Polat Comparison of ANN and RSM modeling approaches for WEDM process optimization", The journal Materials Testing April 2021 DOI: 10.1515/mt-2020-0057

[7] Koeppe, A.; Hernandez Padilla, C.A.; Voshage, M.; Schleifenbaum, J.H.; Markert, B. Efficient numerical modeling of 3D-printed lattice-cell structures using neural networks. Manuf. Lett. 2018, 15, 147–150.

[8] Chao PY, Hwang YD (1997) An improved neural network model for the prediction of cutting tool life. J Intell Manuf 8:107–117.

[9] R. A. Kapgate, V. H. Tatwawadi, "Artificial Neural Network Modelling for Wire-EDM Processing of Aluminium Silicon Carbide Metal Matrix Composite", International Journal of Engineering Research & Technology (IJERT) Vol. 2 Issue 5, May – 2013

[10] S. B. Prajapati, N. S. Patel, V D Asal, "Prediction of Process Parameters of Wire EDM for AISI A2 Using ANN, Volume : 3 | Issue : 5 | May 2013 | ISSN - 2249-555X.

[11] Mangesh R. Phate, Shraddha B. Toney, "Modeling and prediction of WEDM performance parameters for Al/SiCp MMC using dimensional analysis and artificial neural network", Engineering Science and Technology, an International Journal 22 (2019) 468–476.

[12] [12] K. S. Jai Aultrin and M. Dev Anand, "Development of an ANN Model to Predict MRR and SR during AWJM Operation for Lead Tin Alloy", Indian Journal of Science and Technology, Vol 9(13), DOI: 10.17485/ijst/2016/v9i13/90550, April 2016.

[13] Y. M. Elattar1 , M. A. Mahdy2 and H. A. Sonbol , " PREDICTION OF ABRASIVE WATER JET CUTTING PARAMETERS USING ARTIFICIAL NEURAL NETWORK", roceedings of the 18 PT 209 th Int. AMME Conference, 3-5 April, 2018.

[14] Mirko Ficko, Derzija Begic-Hajdarevic, Maida Cohodar Husic , Lucijano Berus, Ahmet Cekic and Simon Klancnik , "Prediction of Surface Roughness of an Abrasive Water Jet Cut Using an Artificial Neural Network", Materials 2021, 14, 3108. https://doi.org/ 10.3390/ma14113108.

[15] P.J.Bagga, M.A.Makhesana, H.D.Patel and K.M.Patel, "Indirect method of tool wear measurement and prediction using ANN network in machining process", Materials today proceedings Volume 44, Part 1, 2021, Pages 1549-1554

[16] M. Hanief,M.F. Wani nad M.S. Charoo, "Modeling and prediction of cutting forces during the turning of red brass (C23000) using ANN and regression analysis", Engineering Science and Technology,an International Journal 20(2017)1220-1226.

[17] R. Sanjeevi a , R. Nagaraja b , B. Radha Krishnan , Vision-based surface roughness accuracy prediction in the CNC milling process (Al6061) using ANN, Materials Today: Proceedings, https://doi.org/10.1016/j.matpr.2020.05.122.

[18] Sherwan Mohammed Najm and Imre Paniti, "Predict the Effects of Forming Tool Characteristics on Surface Roughness of Aluminum Foil Components Formed by SPIF Using ANN and SVR", International Journal of Precision Engineering and Manufacturing (2021) 22:13–26 https://doi.org/10.1007/s12541-020-00434-5.