

NEURAL NETWORK BASED MODELLING FOR PREDICTION OF RESPONSE VARIABLES IN MACHINING PROCESSES: A REVIEW

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Abstract— *The omnipresence of artificial intelligence in manufacturing domain draws the inspiration for the present article. ANN, Fuzzy logic, Genetic algorithm and Support Vector Machines are few of the AI techniques mostly used in manufacturing sector. Present article attempts to review the significant work carried out using Artificial Neural Networks for the prediction of various response variables in the manufacturing domain. ANN is widely used for the prediction purposes owing to its capabilities to handle complex problems without going much into mathematical computations and its similarity with the cognitive system of human beings. The ever rising competition in manufacturing industry calls for the least time investment for maintenance procedures so as to increase the productivity and hence a lot of research is going on to predict the response variables for deciding the optimum cutting parameters.*

Keywords— *Artificial Intelligence, Artificial Neural Network, Turning, Surface Roughness, Fuzzy Logic*

I. INTRODUCTION

Ever since the evolvement of humankind, an urge was felt to sharpen the available stones to cater the basic needs for survival and subsequently leading on those basic steps the dawn of complex machining took place. Since then the contribution of various researchers has led us to develop an understanding of the processes undergone during machining. In the present era, owing to the developments made earlier on, we can make an effort to elaborate the process of machining and the subsequent improvements made in the domain of manufacturing which ranges from actual physical machining to nearly accurate predictions of machining process.

The presence of artificial intelligence is now ubiquitous and the recent improvements made in the field of manufacturing have shown promising results of using AI and machine learning. Artificial neural networks is a branch of machine learning which works on the principle of brain. It is used to develop a model in the same manner in which the brain executes a specific task. Prediction of performance has remained always a matter of interest for researchers since accurate predictions is much epochal for carrying out maintenances and it paves the way for smooth operations, reduction in non-productive time and much more.

For developing performance prediction models using AI, ANN along with fuzzy logic, genetic algorithms, support vector machine (SVM) etc. are mostly used. Among these, use of neural networks seems more assuring owing to the abilities of neural network to model complex process without going much into complex mathematical computations and greater learning abilities along with its similarity with human cognitive system [1]. The beauty of artificial neural networks is that it can successfully predict the nonlinear and noisy response variables. The present article attempts to review the contributions of various researchers in manufacturing field using ANN.

II. ANN STRUCTURE

An ANN model consists of three layers namely input layer, hidden layer and output layer respectively. Each layer consists of specific number of nodes which mimics the human neurons and they are linked with other neurons and thus shares information with each other. These neurons consist of information of weighted process variables. The nodes in the output layer depict the value of response variable. The basic structure of ANN consists of three types of layers in which the programmer feeds the input layer, the hidden layer recognises the pattern and attempts to develop a model by assigning suitable weights to the input parameters so as to reduce the extent of error between the expected and predicted results and the output layer comprises of the expected output values. A neural network is trained and tested with different datasets to ensure the learning and recognising accuracy of the model for arriving at an optimum topology with corrected assigned weights. Figure 1 shows the basic structure of neural network.

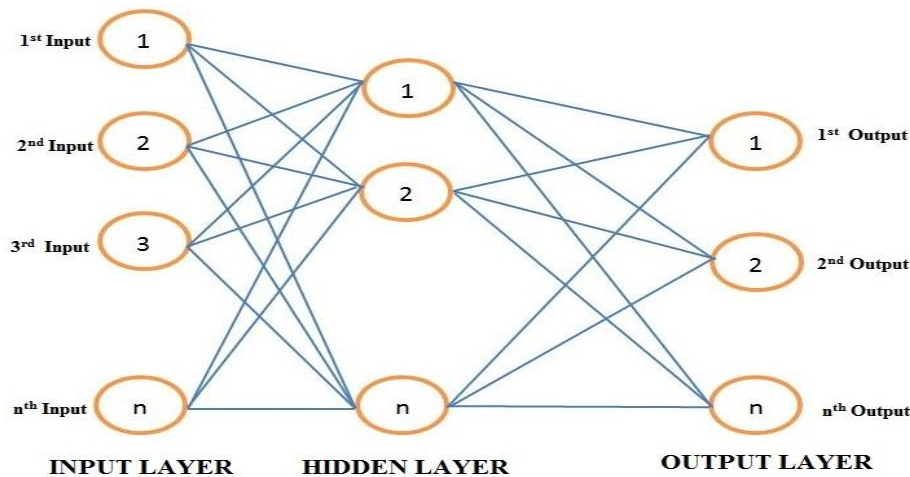


Fig.1: A typical neural network structure

Each connection between the neurons has a synaptic weight or strength, a number which controls the signal between both the neurons. Adjustment of weights depends upon the output expected. If the network generated output is close to the approximated output then there is no need of adjusting the weights. However if the generated output deviates much from the expected output then adjustment in weight becomes necessary till the output value approximates the desired value in the training phase of the network.

III. CURRENT STATUS IN LITERATURE

Arapoğlu et al. [2] observed that the accuracy of regression variable elimination methods reduces to produce accurate results when the number of process variables increases and so an attempt was made to predict the surface roughness considering thirteen process variables. The training of ANN model also holds much significance in the view that if an ANN model is trained with too much data, it gets over trained.

Reddy [3] conducted experimental work to predict the surface roughness considering cutting speed, feed and depth of cut as process variables using Feed-forward back propagation networking with Lavenberg-Marquard algorithm in ANN. Accurate fitness obtained in the form of graphs from MATLAB were considered as a measure of the performance of the training data. The network was trained with two hidden layers and ten hidden neurons to obtain a correlation coefficient of 0.99994. The obtained predicted values were found to be in close proximity with the actual values. It was observed that the surface finish increases with high cutting speeds and low feed rates.

Mandal [4] developed an ANN model to predict tool wear during cryogenic machining. Back propagation technique and feed-forward network algorithm was used considering four hidden layers. It was observed that the mean difference between the experimental output and ANN output is least when the transfer function are 'logsig.', 'tansig', 'logsig.' and 'purelin' respectively. Nearly accurate results were obtained from the model as compared to the actual values.

Abhishek et al. [5] developed an MATLAB code based interface for estimating cutting force in accordance to different process variables. The novelty of the work lies in the development of user interface for which load equation for estimation of cutting force is used and the model has predicted very fair and nearly accurate results as compared to the experimental values.

Aykut [6] developed a model using ANN to predict the magnitude of surface roughness during machining of castamides. Correlation rate of 83.6% was obtained from the developed model. A four-layer network was formed having one layer as input layer, two hidden layers and one output layer. A total of eighty one data sets were used in the study.

Kumar et al. [7] developed ANN model to predict the values of cutting forces in all three directions as well as surface roughness. The experimental work was carried over lathe machine. Mean square error and Mean absolute percentage error (MAPE) were calculated to verify the approximations between the predicted values and the experimental values. The values of regression co-efficient R for the training and testing were 0.99481 and 0.98461 respectively.

Sharma et al.[8] carried out experimental work to predict the surface roughness and cutting force during turning operation considering four process variables (speed, feed, depth of cut and approaching angle). The novelty of work lies in inclusion of approaching angle other than the three conventional process variables. A total of 52 experiments were carried out, out of which the ANN model was trained with 30 data sets and rest were kept for testing the model. Mean

square error and Training time both were recorded for each particular combination of epochs and neurons. Average error of the cutting force model is 5.4%. An overall accuracy of 76.4 % was observed.

Pohokar and **Bhuyar** [9] developed an ANN model to optimize the tool life by considering the cutting parameters (cutting speed, feed and depth of cut) as well as tool parameter (rake angle) as process variables. The data set is obtained from industry. The Decision tool Suite 6.2 was used for the purpose of optimisation. The predicted data and the experimental data holds a close approximation of 90% and hence a correct optimization procedure is ensured.

Chen and **Chen** [10] modelled tool wear prediction using ANN. It was noticed that vibration, cutting force and acoustic emission are the signals that are most often used in the monitoring of tool wear. 2000 training cycles made the rms error to come as low as 0.05 and this was acceptably low considering no effects of any overtraining of data sets. The proposed ANN-ITWP system can well predict the tool wear values with a minimum average error of ± 0.037 mm in comparison to the experimental tool wear values.

Hanief et al. [11] modelled cutting force using ANN and regression analysis. The ANN model was proved to be more accurate as compared to the regression analysis. The statistical methods i.e. R² and MAPE were used to compare the predicted results with the experimental results. Correlation of 0.99690 was observed for the validation of data and 0.99692 was observed for testing of data, respectively. The mean square error was 0.0059 in the developed model.

Zain et al. [12] modelled surface roughness considering cutting speed, radial rake angle and feed as process variables. Correlation coefficient of experimental data and predicted data with ANN model was observed to be 0.555 whereas for the regression model it was observed to be 0.540. Four different network structures were used (3-1-1, 3-3-1, 3-6-1, and 3-7-1). A total of 24 experiments were carried out which could possibly be a reason for low correlation coefficient.

Chaskar et al. [13] modelled profit rate in response to conventional machining process parameters (cutting speed and feed rate) using ANN technique. Back propagation algorithm was used to train the model.

Correa et al. [14] compared Bayesian networks and artificial neural networks for surface roughness in milling operation. Bayesian networks were observed to be easily interpretable and superior to artificial neural network in this field. It was observed that the artificial neural technique does not ensure the convergence to a global minimum.

Nalbant et al. [15] created an artificial neural network for the prediction of surface roughness and also investigated the effects of both types of coatings i.e. Physical vapour deposition (PVD) and Chemical vapour deposition (CVD) over the carbide tool inserts for turning operations. For most of the cases, the predicted values were very close to the approximated values.

Zain et al. [16] reviewed ANN technique for surface roughness prediction. It was observed that ANN can predict the response with as low as 19 datasets but higher number of datasets for training and testing can produce much accurate results.

Sonar et al. [17] studied the performance of a radial basis function neural network for predicting the surface roughness in a turning process. The novelty of work lies in inclusion of mechanical vibration as an input for the ANN model. The work paves the way for inclusion of uncontrollable response variables as input in ANN modelling and hence is epochal in the field of neural networks training. The performance of the radial basis function network was observed to be slightly inferior as compared to multi-layer perceptron neural network.

Grzesik and **Brol** [18] assessed the surface quality in turned, honed and ground specimens using statistical, fractal and neural network-based approaches. The inclusion of cutting force as an input for ANN draws attention for the possibility of using it as input parameter. The network comprises of seven input neurones along with seven output neurones interlaced by three hidden layers, each of them with 72 nodes. A 7-72-72-72-7 net topology was selected.

Sharma et al. [19] developed a model for tool wear estimation in turning operations using Adaptive Neuro fuzzy Inference system (ANFIS). Time, cutting forces (F_z), Vibrations (acceleration) and acoustic emissions were used as the input parameters. Acoustic emissions and vibration signals were decoded and used for the detection of the wearing of tool. It was observed that the vertical accelerations were initially more and subsequently reduced during the stable cutting conditions and ultimately started to increase with increase in tool wear.

Wang et al. [20] used wavelet transforms and fuzzy technique for monitoring tool condition with current signals obtained from the spindle motor and feed motor. When a tool was on the verge of breaking, some moderate spikes were observed by the feed motor current signals. When the tool broke, a huge spike appeared in the current signals, and subsequently the following signals were not smooth.

Kant and Sangwan [21] developed an alternate coupled model for predicting the optimal values of cutting parameters which results in minimizing the surface roughness. They developed a predictive and optimisation model by pairing two machine learning techniques, ANN and genetic algorithm (GA) respectively. The predicted results were very nearer to the experimental values and mean absolute error of 4.11 percentages indicates that the developed model was quite accurate in predicting the surface roughness values. The results of ANN were compared with results of Fuzzy logic and regression models. It was observed that ANN was superior as compared to FL and regression models.

Sangwan et al. [22] also integrated ANN with genetic algorithm aiming for improved efficiency and effectiveness. The neural network was modelled in MATLAB tool box. The genetic algorithm was used for optimising the process parameters for minimising the surface roughness. ANN-GA coupled model was observed to be capable of predicting nearly accurate values. The Levenberg- Marquadt (LM) algorithm was used for training the algorithm alongwith hyperbolic tangent sigmoid transfer function as transfer function. Back propagation algorithm was used to train the network. Mean absolute percentage error (MAPE) was found to be reduced to 1.79 from 4.30 upon considering ANN over RSM.

Benardos and Vosniakos [23] developed an ANN model for the prediction of surface roughness in CNC face milling. The experimental work was conducted using design of experiment obtained from Taguchi method. Depth of cut, feed rate per tooth, the engagement and wear of the cutting tool, cutting speed, the use of cutting fluid and the three components of the cutting forces were considered as the cutting process parameters. The Neural network was trained with the Levenberg- Marquardt algorithm. The mean square error was found to be 1.86%.

Benardos and Vosniakos [24] highlighted the various approaches and practices that are used for the prediction of surface roughness. The classification of the approaches were done on the basis of design of experiments (DOE), machine theory, artificial intelligence (AI) and experimental investigation. Surface roughness was stated as the third to sixth order deviation from the normal surface. It was observed that most commonly feed forward ANNs are used and they are trained with some variation of the back propagation algorithm. The advantages and disadvantages of each approach were well mentioned and the use of AI was emphasised for predictions. The ANN has got the advantage of dealing noisy and incomplete data easily.

Cus and Zuperl [25] highlighted the capability of ANNs for the purpose of optimisation of machining parameters. They considered the technological, economical and organisational limitations and developed an algorithm to assure efficient optimization of turning parameters and to achieve highly precised predicted values. The proposed system was easily expandable for grinding, drilling, milling etc. It was observed that the multi-layer feed forward neural network has proven itself to be a superior approximator of non-linear functions. It was advised to refrain from the use of neural networks for optimisation if enough time is available for deep analysis.

Hossain and Ahmad [26] designed Adaptive Network-based Fuzzy Interface System (ANFIS) for the modelling and prediction of surface roughness in three dimensional milling operations. A total of 84 datasets were generated and out of which 68 datasets were used as training datasets and rests were used for the testing purpose. The performance of the developed model was judged by the statistical tools of mean square error and mean absolute percent error. It was observed that the ANFIS system outperformed ANN and RSM and the proper quantity of data sets could ensure better training of model for testing and training.

Beatrice et al. [27] developed prediction model for predicting surface quality in hard turning of AISI H13 steel alongwith minimal cutting fluid application. Neural networks were trained and tested with varying architectures and the root mean square error was the selection criteria for determining the suitability of the model. 2 hidden layers were used to arrive at the best solution. Network having structure 3-7-7-1 gave the lowest RMSE value. The values predicted by the ANN model were in close approximation to the experimental values.

Davim et al. [28] developed ANN model for the prediction of surface roughness considering cutting speed, feed and depth of cut as the input parameters for the model. The planning for the experiments was done in accordance to L27 orthogonal array. 3 dimensional surface plots were generated to study the effects of interaction of cutting parameters on surface quality. It was observed that surface quality was significantly affected by the speed and feed rate whereas depth of cut have the least effect on surface quality.

Saini et al. [29] attempted to predict the tool wear face milling operation of Ti6Al4V alloy and analysed the vibration signatures using support vector machines to correlate the flank wear for the same length of cuts. The training and testing of the model shared 70% and 30% of the data set obtained experimentally. The fine Gaussian SVM model provided 63.3% accuracy.

Kumar and Sarathe [30] reviewed various surface roughness prediction techniques and suggested that AI systems are among the most suitable solution for the precise and quick predictive model. It was observed that the coupled models such as ANFIS shows better accuracy than the single AI technique.

IV. CONCLUSIONS

Artificial intelligence is wide spread and its use in condition monitoring of machining operations paves the way for the predictive maintenance of machine structures which is epochal in the era of cut throat competition in manufacturing sector. ANN is generally used to predict the surface roughness considering cutting speed, feed and depth of cut as input parameters. The results predicted by ANN models approaches closely to the experimental values. The literature presented concludes the superiority of ANN as compared to mathematical regression models. Coupling of two or more AI techniques for prediction and optimization can go a long way ahead.

REFERENCES

- [1] A. Kohli and U. S. Dixit, "A neural-network-based methodology for the prediction of surface roughness in a turning process," *International Journal of Advanced Manufacturing Technology*, vol. 25, no. 1–2, pp. 118–129, 2005.
- [2] R. A. Arapoğlu, M. A. Sofuoğlu, and S. Orak, "An ANN-Based Method to Predict Surface Roughness in Turning Operations," *Arabian Journal for Science and Engineering*, vol. 42, no. 5, pp. 1929–1940, 2017.
- [3] M. V. K. Reddy, "Use of Artificial Neural Networks to Investigate the Surface Roughness in CNC Milling Machine," *International Journal of Science and Research*, vol. 3, no. 5, pp. 1248–1252, 2014.
- [4] K. K. Mandal, "Development of an ann model to predict surface roughness during cryogenic machining operation," *International Journal of Research in Engineering and Technology*, vol. 3, no. 7, pp. 393–397, 2014.
- [5] K. Abhishek, K. Dj, P. Kavalur, and N. H. Akshay, "ANN modeling for prediction of cutting force component during orthogonal turning," *International Research Journal of Engineering and Technology*, vol. 05, no. 06, pp. 1176–1181, 2018.
- [6] Ş. Aykut, "Surface roughness prediction in machining Castamide material using ANN," *Acta Polytechnica Hungarica*, vol. 8, no. 2, pp. 21–32, 2011.
- [7] S. Kumar, R. Singh, A. R. Dixit, A. Mandal, and A. Das, "Response prediction in machining of AISI 1040 stainless steel using ANN model," *ARPJ Journal of Engineering and Applied Sciences*, vol. 11, no. 16, pp. 10117–10122, 2016.
- [8] V. S. Sharma, S. Dhiman, R. Sehgal, and S. K. Sharma, "Estimation of cutting forces and surface roughness for hard turning using neural networks," *Journal of Intelligent Manufacturing*, vol. 19, no. 4, pp. 473–483, 2008.
- [9] N. Pohokar and L. Bhuyar, "Neural Networks Based Approach for Machining and Geometric Parameters optimization of a CNC End Milling," *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 3, no. 2, 2014.
- [10] J. C. Chen and J. C. Chen, "An artificial-neural-networks-based in-process tool wear prediction system in milling operations," *International Journal of Advanced Manufacturing Technology*, vol. 25, no. 5–6, pp. 427–434, 2005.
- [11] M. Hanief, M. F. Wani, and 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*, vol. 20, no. 3, pp. 1220–1226, 2017.
- [12] A. Mohd Zain, H. Haron, and S. Sharif, "Application of regression and ANN techniques for modeling of the surface roughness in end milling machining process," *Proceedings - 2009 3rd Asia International Conference on Modelling and Simulation, AMS 2009*, no. March 2015, pp. 188–193, 2009.
- [13] P. R. Chaskar, A. S. Lad, J. K. Mane, A. Sangre, and M. S. Kirkire, "Optimization of CNC Milling Parameters Using ' Artificial Neural Network ,' " *Imperial Journal of Interdisciplinary Research*, vol. 3, no. 2, pp. 683–687, 2017.
- [14] M. Correa, C. Bielza, and J. Pamies-Teixeira, "Comparison of Bayesian networks and artificial neural networks for quality detection in a machining process," *Expert Systems with Applications*, vol. 36, no. 3 PART 2, pp. 7270–7279, 2009.
- [15] M. Nalbant, H. Gökkaya, I. Toktaş, and G. Sur, "The experimental investigation of the effects of uncoated, PVD- and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural networks," *Robotics and Computer-Integrated Manufacturing*, vol. 25, no. 1, pp. 211–223, 2009.
- [16] A. M. Zain, H. Haron, and S. Sharif, "Review of ANN Technique for Modeling Surface Roughness Performance Measure in Machining Process," in *2009 Third Asia International Conference on Modelling & Simulation*, pp. 35–39, 2009.
- [17] D. K. Sonar, U. S. Dixit, and D. K. Ojha, "The application of a radial basis function neural network for predicting the surface roughness in a turning process," *International Journal of Advanced Manufacturing Technology*, vol. 27, no. 7–8, pp. 661–666, 2006.
- [18] W. Grzesik and S. Brol, "Hybrid approach to surface roughness evaluation in multistage machining processes," *Journal of Materials Processing Technology*, vol. 134, no. 2, pp. 265–272, 2003.
- [19] V. S. Sharma, S. K. Sharma, and A. K. Sharma, "Cutting tool wear estimation for turning," *Journal of Intelligent Manufacturing*, vol. 19, no. 1, pp. 99–108, 2008.
- [20] Jun Wang, Shiu Kit Tso, and Xiaoli Li, "Real-time tool condition monitoring using wavelet transforms and fuzzy techniques," *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, vol. 30, no. 3, pp. 352–357, 2000.

- [21] G. Kant and K. S. Sangwan, "Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm," *Procedia CIRP*, vol. 31, pp. 453–458, 2015.
- [22] K. S. Sangwan, S. Saxena, and G. Kant, "Optimization of machining parameters to minimize surface roughness using integrated ANN-GA approach," *Procedia CIRP*, vol. 29, pp. 305–310, 2015.
- [23] P. G. Benardos and G. C. Vosniakos, "Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments," *Robotics and Computer-Integrated Manufacturing*, vol. 18, no. 5–6, pp. 343–354, 2002.
- [24] P. G. Benardos and G. C. Vosniakos, "Predicting surface roughness in machining: A review," *International Journal of Machine Tools and Manufacture*, vol. 43, no. 8, pp. 833–844, 2003.
- [25] F. Cus and U. Zuperl, "Approach to optimization of cutting conditions by using artificial neural networks," *Journal of Materials Processing Technology*, vol. 173, no. 3, pp. 281–290, 2006.
- [26] S. J. Hossain and N. Ahmad, "Artificial Intelligence Based Surface Roughness Prediction Modeling for Three Dimensional End Milling," *International Journal of Advanced Science and Technology*, vol. 45, no. September, pp. 1–18, 2012.
- [27] B. Anuja Beatrice, E. Kirubakaran, P. Ranjit Jeba Thangaiah, and K. Leo Dev Wins, "Surface roughness prediction using artificial neural network in hard turning of AISI H13 steel with minimal cutting fluid application," *Procedia Engineering*, vol. 97, pp. 205–211, 2014.
- [28] J. P. Davim, V. N. Gaitonde, and S. R. Karnik, "Investigations into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models," *Journal of Materials Processing Technology*, vol. 205, no. 1–3, pp. 16–23, 2008.
- [29] A. Saini, D. Goyal, B. Pabla, and S. Dharmi, "Intelligent tool wear monitoring in machining Ti6AL4V alloy using support vector machines," *Communication and Computing Systems – Prasad et al. (Eds) © 2017 Taylor & Francis Group*, no. November, pp. 499–505, 2017.
- [30] Manikant Kumar and Dr. A. K Sarathe, "Prediction of Surface Roughness on CNC Machine: A Review," *International Journal of Engineering Research and*, vol. V5, no. 07, pp. 300–307, 2016.