

Modelling of CO₂ Laser Materials Processing by Networked Neuro-Dimension Fuzzy Intelligent System

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Abstract: The usage of non-contact machine tools in metal cutting industries is increasing exponentially in recent times due to the advent of super hard work materials. The fiercely competitive manufacturing industries find the traditional trial-and-error method, not only challenging and time consuming but also economically nonviable in acquiring superior quality of end products produced from such materials. This paper presents a more accurate prediction method for surface roughness values by using Networked Fuzzy Intelligent System (N-FIS) in combination with the commercial software tools, Matlab and Neuro-Dimension Network. Experiments were conducted on manganese molybdenum pressure vessel plates to validate the robustness of the developed model in forecasting the surface roughness values. The predicted results were found to be reasonably accurate with an error percentage well below 10% for almost all runs at the prediction stage. On the other hand, the experimental validation results for selected critical runs were found to be extremely promising with results of an accuracy of more than 90%. It was concluded that the setting of proper network algorithm and rules, can actually help the industry to perform laser machining better by saving huge waste materials by employing the approach presented in this paper as compared to the traditional trial-and-error method.

Key words: Laser modelling, Laser cutting, Fuzzy logic, Networked fuzzy

INTRODUCTION

Conventional materials processing modelling techniques are being challenged especially for complex and advanced machine tools which process high number of processing parameters. Thus, many intelligent approaches are being embarked to perform diligent quality and performance prediction. In this paper, the Networked fuzzy intelligent system (N-FIS) was successfully used in this research to predict the cut quality of manganese molybdenum (MnMo) boiler plate utilizing complex laser machining process. In laser machining, surface roughness is one of the most important quality evaluation factors, generally dependent upon the physical and mechanical properties of the materials being cut, material thickness, focal length, standoff distance, cutting speed, the type of cutting gas and gas pressure.

In addition to this, the nonlinear behavior of the laser-material interactions also plays a significant role in forming the final surface profile and the resultant geometry of the machined micro-features. Moreover, process modelling with huge number of parameters using conventional, analytical and numerical methods too poses a substantial challenge. By modelling the complex material processing by N-FIS, the traditional trial-and-error or one factor at a time (OFAT) approach which are not only be costly but also time consuming could very well be avoided. Thus, the ability to predict surface roughness quality accurately and effectively by this modelling technique ultimately improves the engineering of component machining, reducing significant machining cost up to 70% of the overall manufacturing cost (Arata Yoshiaki, *et al.*, 1979; Zhang, W., *et al.*, 2001; Yousef, F., *et al.*, 2003; Ming-Jong Tsai, *et al.*, 2008). Recent research activities in precision machining shows that artificial neural network (ANN) has powerful pattern classification and recognition which can be well suited for problems whose solutions require knowledge that is difficult to specify by human (Ciurana J., G. Ariasb, and T. Ozel, 2009). Fuzzy rule acquisition method was also used for tool wear estimation using radial basis networks to find the optimal combined rules to compose fuzzy reasoning mechanism (Xiaoli Li, *et al.*, 2004). A CNC tool wear detection using neuro-fuzzy classification system has been successfully investigated by employing three different types of membership function (Hahn-Ming Lee, *et al.*, 1999). Tool-failure detection system was analytically modelled for turning of metal matrix composite (Kishawy, H.A., *et al.*, 2004). Model using neuro-adaptive learning techniques which is similar to those of neural network was originally presented by Jang (Milos

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Madic and Miroslav Rodovanovic, 2012). Hybrid genetic and SVD methods were also used to design adaptive networks (Nariman-Zadeh, N., *et al.*, 2006) and adaptive network fuzzy inference system to predict surface roughness in end milling (Ship-Peng Lo, 2006). The same network was reported to have also successfully used to predict square hole profiles (Fung-Huei Yeh, *et al.*, 2006). Optimization of CO₂ laser machining was performed by combining Taguchi and Neural Network (Ching Been Yang, *et al.*, 2012) and parameter optimization was also reported to have been performed onto non-vertical laser cutting (Chen Jimin, *et al.*, 2007). ANN-Hybrid model was employed in modelling of Laser Assisted Oxygen Cutting of mild steel plate (Chaki, S., and S. Ghosal, 2011). Grey-Fuzzy methodology was employed successfully in modelling of multiple quality investigation of laser cutting (Pandey, A.K. and V. K. Dubey, 2012), while graphical user interface (GUI) modelling was developed to ease the artificial intelligence modelling phases (Sivarao, Peter Brevern, and N.S.M. El-Tayeb, 2009). Reviews of AI applications in laser cutting qualities are expressed as explicit nonlinear functions of the laser control parameters to improve the prediction accuracy (Chaudhari, P.S., *et al.*, 2012).

In general, the selection of optimum machinability data for a specific machine tool plays the most important role in manufacturing, as the process control parameters of a machine tool are not always precisely understood. Thus, it becomes increasingly difficult to recommend the optimum values with a huge variety of expensive materials in the market. As to propose a new solution to these challenges, this research work presents the adoption of Networked Fuzzy Intelligent System (N-FIS) to model and control critical machining parameters of a CO₂ laser cutting machine desiring excellent surface roughness of MnMo boiler plates. The schematic diagram of laser cutting principle shown in Figure 1 clearly indicates the position and profiling of a work while the real cutting of CO₂ laser on a sacrificial table is shown in Figure 2.

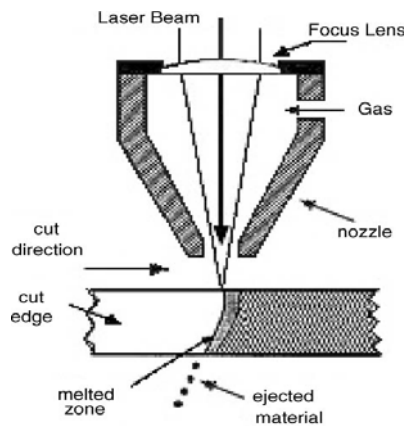


Fig. 1: CO₂ laser cutting.



Fig. 2: Profiling of CO₂ laser on sacrificial table

MATERIALS AND METHODS

Selection of Materials and Process Control Parameters:

For conducting the experimental runs, grade B, manganese-molybdenum (MnMo) pressure vessel plates with tensile Strength of 690 MPa were used. Seven process controlling parameters, viz., the standoff distance, focal distance, gas pressure, power, cutting speed, frequency, and duty cycle were selected for the investigation.

The gas nozzle with 0.5 mm diameter and a focused beam diameter of 0.25 mm were used for the study. The dimensions of the prepared plate were kept as 1.2×0.7 m (length $\times$ width). A total of 128 experiments were conducted based on the DOE matrix developed with 2^k full factorial design, where, k represents number of factors (7 independent process control parameters) and 2 represents level (low, coded as -1 and high, coded as +1). The units, symbols, and the limits of the factors (control parameters) are given in Table 1.

Table 1: Process control parameters and their limits

No.	Control Parameter	Unit	Notation	Low		High
1	Power	W	<i>P</i>	2500		2800
2	Cutting speed	RPM	<i>S</i>	800		1200
3	Frequency	Hz	<i>F</i>	800		1000
4	S.O.D	mm	<i>SOD</i>	1		1.5
5	F.D	mm	<i>FD</i>	0		1
6	Pressure	bar	<i>Pr</i>	0.7		1
7	Duty cycle	%	<i>D</i>	40		80

All experimental data sets and the objective functions were programmed into the networked fuzzy system on Matlab platform. The details of the laser machine, machining condition (parameter control), the apparatus used for data collection ('Ra' observation), work material, and data collection interpretation are given in Table 2.

Table 2: Specification for the Laser Machine

Laser machine Model	Helius Hybrid 2514 CO ₂ Laser
Controller	FANUC Series 160 i-L
Maximum capacity	4 kW
Laser source	N ₂ (55%), He (40%) & CO ₂ (5%) with purity 99.995%
Gas mixture Pressure	3 bar (max)

The experimental procedures, data collection, analysis, etc. are conducted as per the standard recommendations of 'Laser Cutting of Metallic Materials' German Standard, DIN 2310-5. Mitutoyo surf test SJ301 with a sampling range of 0.8 – 8 was used for all profile measurements. This work comprises of N-FIS modelling methodology and parametric methodology. The initial work was focused on how the Fuzzy is networked into intelligent system, and later to determine how the entire experimental work was performed to achieve the outlined research objectives. The modelling methodology was used for screening & modelling which caters the initial work in establishing the N-FIS model. On the other hand, parametric methodology was designed for eventual full experimental and validation purpose.

Modelling:

The modelling process shown in Figure 3 was initiated by executing networked fuzzy parameter to select 'membership type' together with its 'optimization method'. The epoch number is then simulated to prevent over-fitting, where this will optimize and suggest the best epoch number for the selected settings and model. Later, the data is trained to observe the root mean square error (RMSE) and average percentage error (APE) values to the desired satisfactory level. Once the desired value is achieved, the modelling would be finalized and machining parameters can be fully loaded. The comparative of the predicted vs. observed can be displayed upon demand. The input laser parameters can be tested for interpolation and extrapolation levels to validate the trained model.

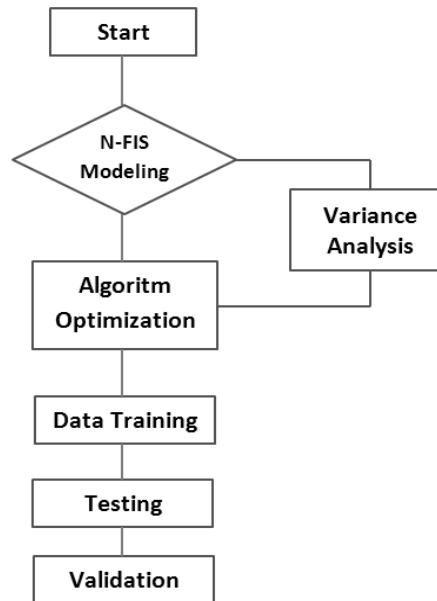


Fig. 3: Modelling Methodology

Parametric Process:

The employed parametric process is shown in the form of workflow (Figure 4). It involves few sequential primary works where, the work materials supplied and sponsored by the boiler consultancy industry, Kara Pte. Ltd. was screened according to machine-material suitability. Then after, the processing parameters have been screened by fractional factorial analysis to discard non-contributing parameters out of 14 available on the machine. The analysis found seven significant parameters which are classified as design parameters. Those significant parameters were then explored to attain bracket values to capture parameter work range. The DOE experimental matrix was then established by 2^k full factorial design. The experimentations were then randomized to cross run with their run orders preventing bias results and to test the machine repeatability by providing huge differences in transverse movement between laser head and sacrificial table. All the experiments and observations were carried out based standard recommendations of DIN 2310-5 and DIN EN ISO 9013:2000 respectively to fit the requirement of sponsored industry. The observed results were then analyzed for unexpected / unintended errors. Thus, the experimentation sets with huge variance in response is most likely to be caused by technical errors and they were repeated to ensure it does not caused by human error. Once the 128 experimental values were satisfied, 60% of them were used for training and test the network fitness while remaining 40% were used for testing and validation. Thus, eight different network architectures were tested with various sets of architectures on network simulating software, namely Neuro-Dimension where, the seven input parameters were maintained with singleton output. The network with lowest RMSE value was then selected as final and optimized for the use of this research. Then after, 15 predictions with the intervals of 10 were experimentally validated to confirm the ability of developed intelligent model in achieving the individual percentage accuracy above 90% as targeted at the beginning of this study.

Hybrid Artificial Intelligence-Expert System:

Two artificial intelligent tools were hybridized to gain the beneficial/strength of them both. Neural tool which is widely known of having the ability to train the data sets could provide the best network for the desired responses with the most minimum errors by taking into account the weights, neurons and their iterations. On the other hand, Fuzzy Logic (FL) which is also known as expert system is able to create the functions between fields to provide best responses based on rules provided by field expert. Knowing the limitation on Fuzzy which could not train the data while ANN limits the human intervention in setting the rules, the combination added of Fuzzy and NN is taken advantage by customizing their behavior and capability.

Fuzzy Logic:

Fuzzy logic (FL) suits very well in defining the relationship between inputs and desired outputs of a system, where its extra ordinary controlling and reasoning capability made its way to the application of many complex industrial systems for precise modelling under various assumptions and approximations. Fuzzy system consist few inputs, output(s), set of predefined rules and a defuzzification method with respect to the selected fuzzy

inference system. Mamdani Fuzzy Inference System (FIS) is the most known or used in developing fuzzy models. The output of the system is generally defuzzified resulting fuzzy sets are combined using aggregation operator from the consequent of each rule of the input.

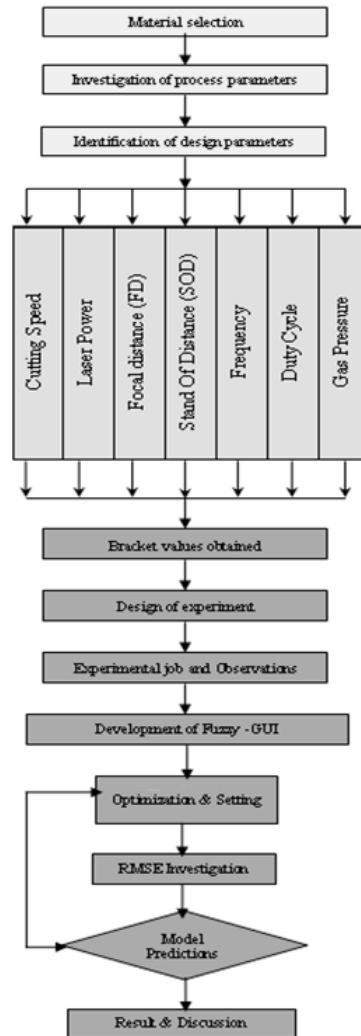


Fig. 4: Experimental methodology

A single if-then rule is written as;

IF “X” is A, THEN “Y” is B

or;

$$\{IF(premise_i)THEN(consequent_i)\}_{i=1}^N$$

where, A and B are linguistic values defined by fuzzy sets on the ranges; X and Y, respectively. The if-part of the rule “x is A” is called the antecedent or premise, while the then-part of the rule “Y is B” is called the consequent or conclusion. The defuzzification method (Figure 5) applied onto a fuzzy model based on three different conditions.

In this research, the input membership function (Figure 6) was divided into two linguistic values, where each input denoted as low and high respectively. The determination of the membership function is done on Matlab. This technique enabled excellent model development for non-linear process in which the rules were automatically generated under adaptive network environment.

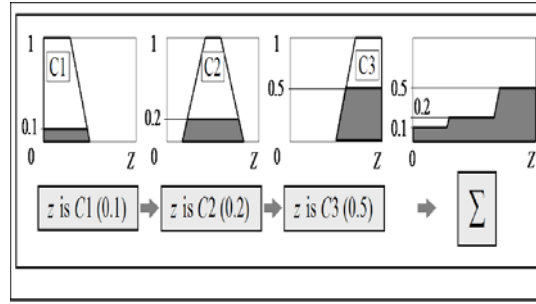


Fig. 5: Defuzzification using Mamdani FIS

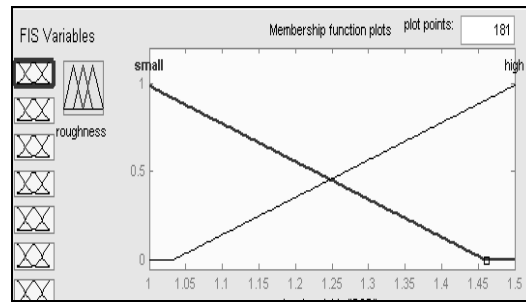


Fig. 6: Input MF for fuzzy model

The membership function and set of rules were fed into the system to predict the responses. Each rule in the system is considered very important and critical to generate the predictions in numeric form. The snapshot of the membership function plot (Figure 6) and dynamic mode rules fed into the system (Figure 7) is possible to be visualized for customization. Knowing the non-linear behavior of laser processing, 128 self-generated rules were set to ensure the desired outputs are reliable and satisfactory.

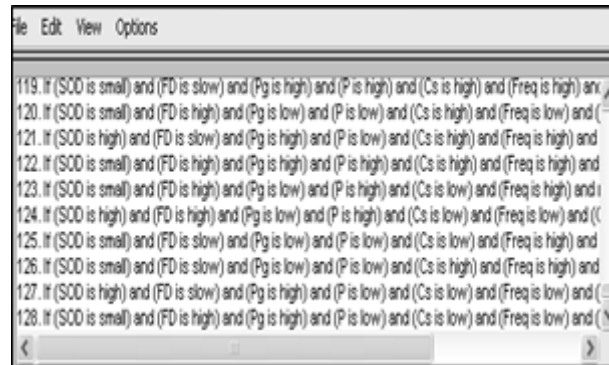


Fig. 7: Part of the self-generated fuzz rules

Neuro Dimension Network:

Neuro-Dimension Network was programmed for automatic reasoning to enhance the modelling competence as compared to their individual capability. It was able to model non-linear system, robustness to noisy data, and generic modelling capability. Since the prediction of the cut quality was the primary aim, the Neuro- Dimension Network models were initially optimized based on training and testing over all the observed data sets before the integration on different platform. The complete experimental data sets have been used to train the network, where the learning process was stopped after 500 iterations. The number of neurons and layers were calculated automatically based on the network training error. The first step of the analysis is to normalize the raw input data to values between 3 and 40 is shown by (1).

$$x_i = \frac{40}{d_{\max} - d_{\min}} (d_i - d_{\min}) + 3 \quad (1)$$

The d_{max} and d_{min} are the maximum and minimum inputs and d_i is i^{th} input. Input of i^{th} neuron on hidden layer I_{yi} , calculated by,

$$I_{yi} = \sum_{i=1}^M w_{xy} x_i \quad (2)$$

M is number of neurons in input layer and w_{xy} is numerical weight value of the connection between the two neurons. x_i is i^{th} normalized output from the input layer. The output of the i^{th} neuron on hidden layer y_i is to be calculated by applying an activation function to the summed input of that neuron. The output of i^{th} neuron on hidden layer then appear as,

$$y_i = f(I_{yi}) = \frac{1}{1 + e^{-s(I_{yi})}} \quad (3)$$

The s is the slope of the sigmoid function and the values received by the output layer I_z are outputs of the hidden and input layers.

$$I_{zi} = \sum_{i=1}^M w_{xz} x_i + \sum_{i=1}^N w_{yz} y_i \quad (4)$$

M and N are the numbers of neurons in the input and hidden layers. w_{xz} and w_{yz} are corresponding weights from the input to the output layer and from hidden layer to output layer. The actual output in the output layer is calculated by applying the same sigmoid function as applied for hidden layer.

$$z_i = f(I_{zi}) \quad (5)$$

Error between the desired and actual output in the output layer is given by

$$\delta_{zi} = f'(I_{zi})(T_i - Z_i) \quad (6)$$

Where, T_i is the i^{th} training input to the neuron and f' is the derivative of the sigmoid function. For each neuron on the hidden layer, the error, δ_{yi} is

$$\delta_{yi} = f(I_{yi}) \sum_{i=1}^L \delta_{zi} w_{yz} \quad (7)$$

where,

the L is number of neurons in the output layer.

A total of eight nearly possible networks were trained and tested (Figure 8) for the output based on fitness and test error comparisons among them. Networked Fuzzy intelligent system has been developed by importing a trained and optimized network into Matlab environment to predict the surface roughness. The network is able to predict data using Networked Fuzzy Intelligent System synchronizing hybrid and back propagation optimization method. Seven corresponding input parameters namely; power, speed, pressure, focal distance, standoff distance, frequency, duty cycle were used to investigate quality of surface roughness by training and validation. The optimized 7-13-1 network (Figure 9) has been established upon few critical screening stages of other tested networks considering their respective RMSE values.

ID	Architecture	# of Weights	Fitness	Train Error	Validation Error	Test Error	AIC
2	[7-18-1]	163	5.470586	0.133435	0.092195	0.182796	-245.25013
3	[7-11-1]	100	5.840169	0.119474	0.091359	0.171228	-380.97524
4	[7-7-1]	64	5.731579	0.120591	0.090985	0.174472	-452.15644
5	[7-15-1]	136	5.614985	0.125033	0.092011	0.178095	-304.97341
6	[7-13-1]	118	6.804306	0.094149	0.094925	0.146966	-365.9391
7	[7-14-1]	127	5.789575	0.11389	0.107203	0.172724	-331.18766
8	[7-12-1]	109	5.740716	0.110456	0.097735	0.174194	-369.88190

Fig. 8: Evaluated eight sets of developed networks

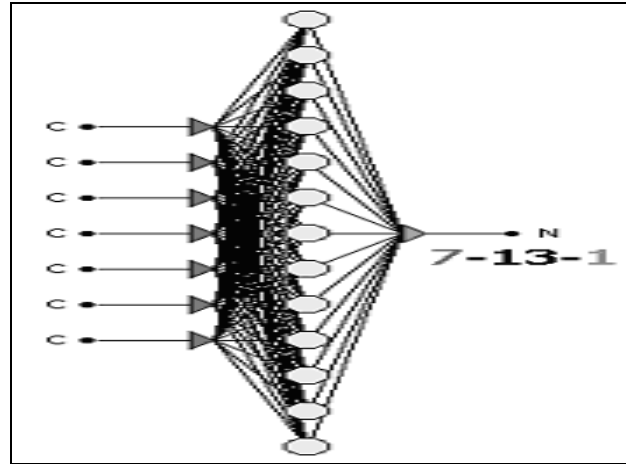


Fig. 9: The 7-13-1 architecture with 7 inputs, 1 hidden layer with singleton output

The specially developed Neuro-Dimension functions provides the fullest output of rule to network emerging capability in few simple steps even for a complex process such as laser machining. The key features of the networked fuzzy output are; over-fitting, surface modelling, rule viewer, membership function and comparative scatter plot. It is programmed to train 5.0mm thickness work material and predict their responses using those seven inputs. The ability to predict the data accurately is based on the setting used to train the data.

RESULTS AND DISCUSSION

The experimentally observed surface roughness (Ra) values were fed into the optimized 7-13-1 N-FIS network to validate the network's ability in predicting as desired. Thus, it was programmed in Matlab software to generate the graph (Figure 10) that compares the observed and predicted values. The highest percentage error between the observed and predicted values was found to be less than 11%. Thus the model was considered to be in accepted range and 15 additional predictions were made for experimental validation within the range of experimental values. Setting the machining parameters to the modelling environment, the work material was cut to experimentally validate the responses. The values obtained are tabulated in Table 3. As clearly seen from the Table 3 the individual experimental validation percentage were found to be all well below 10 % while the average deviation and percentage error were 4.72 and 0.48 microns respectively. The bar chart that plots the predicted and experimental validation results for selected experiment number is shown in Figure 11. The experiments were purposely selected with huge difference in their parametric values so that the robustness of the model could be tested. Even then, the predictive results as compared to the experimentally validated resulted in good agreement conforming to the results gain in predicting historic data gained from initial experimentations.

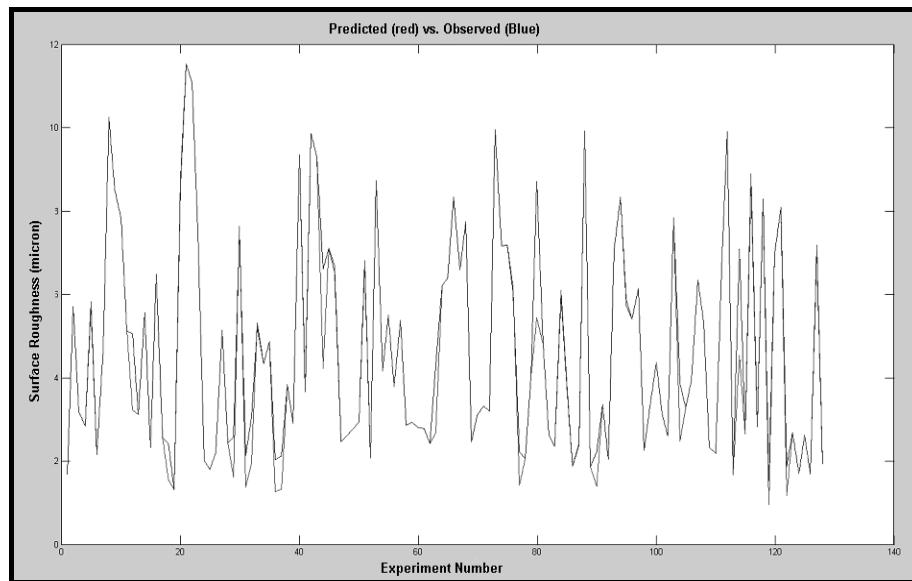


Fig. 10: Observed versus networked fuzzy model predicted results for surface roughness

Table 3: Numeric of selected modelling and validation data

Run	Expn. No.	Predicted (micron)	Validation (micron)	Deviation (micron)	Exp'n Validation Error (%)
1	1	1.99	1.85	0.14	7.30
2	10	6.32	6.26	0.06	1.02
3	20	5.97	5.51	0.46	8.37
4	30	7.95	8.25	0.30	3.64
5	40	4.31	4.38	0.07	1.55
6	50	5.83	5.56	0.27	4.86
7	60	3.25	3.42	0.17	4.97
8	70	7.38	6.85	0.53	7.74
9	80	4.04	4.15	0.11	2.58
10	90	5.74	5.92	0.18	3.04
11	100	4.47	4.09	0.38	9.29
12	110	4.86	4.59	0.27	5.88
13	120	4.42	4.51	0.09	2.00
14	125	6.58	6.24	0.34	5.45
15	128	3.34	3.45	0.11	3.19
Total Average:				0.48	4.72

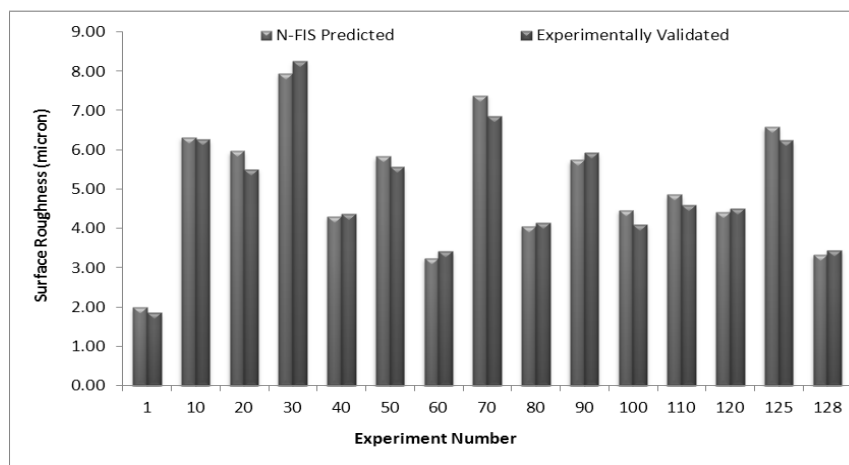


Fig. 11: Manual plot of N-FIS modeled vs. experimentally validated values for surface roughness.

The research results/output therefore, can be considered to be beneficial due to the fact that the prediction accuracy achieved from the method presented in this paper was more than 90 %, which is about 10% better than

the expected values prescribed by DIN and TRIUMPF German Standards. From the comparative analysis, it was confirmed that the developed networked fuzzy modelling with precise Fuzzy expert rules and better neuro network selection with proper connections and algorithms could make precise predictions and validations which has practically proved that this method could be considered as a much better intelligent modelling approach. The standalone neural network and fuzzy expert systems hence can very well be challenged by this proposed networked fuzzy system in predicting the quality of materials processing on advanced non-linear machine tools with huge number of controllable parameters.

Conclusion:

This work confirmed the superiority of Networked Fuzzy Intelligent System (N-FIS) in predicting surface roughness of MnMo boiler plates processed by CO₂ laser cutting machine. Since laser-cutting qualities are expressed as explicit nonlinear functions of the laser control parameters which often requires highly skilled labor combined with vast knowledge in work materials, their physical and mechanical properties and behavior the proposed modelling technique could be very well beneficial to the Industry. However, this method has only been used in a preliminary level by most of the industries. It can be further explored to establish robust model for wide range of applicable advanced materials in future.

ACKNOWLEDGEMENT

The authors would like to thank the Ministry of Higher Education (MOHE), Malaysia for providing the research grant (grant number: F0084 & G00010). The authors would also like to sincerely thank Universiti Teknikal Malaysia Melaka (UTeM) for providing the continuous encouragement and support in motivating them towards developing new findings from time to time. They are also highly indebted to Kara Engg. Pte. Ltd., and to Ir. Vijay for partially funding this project and sponsoring MnMo work materials, together with laser processing expert, in guiding them to develop expert rules into Fuzzy system.

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