Neural Network Multi Layer Perceptron Modeling For Surface Quality Prediction in Laser Machining

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1. Abstract

Uncertainty is inevitable in problem solving and decision making. One way to reduce it is by seeking the advice of an expert in related field. On the other hand, when we use computers to reduce uncertainty, the computer itself can become an expert in a specific field through a variety of methods. One such method is machine learning, which involves using a computer algorithm to capture hidden knowledge from data. The researchers conducted the prediction of laser machining quality, namely surface roughness with seven significant parameters to obtain singleton output using machine learning techniques based on Quick Back Propagation Algorithm. In this research, we investigated a problem solving scenario for a metal cutting industry which faces some problems in determining the end product quality of Manganese Molybdenum (Mn-Mo) pressure vessel plates. We considered several real life machining scenarios with some expert knowledge input and machine technology features. The input variables are the design parameters which have been selected after a critical parametric investigation of 14 process parameters available on the machine. The elimination of non-significant parameters out of 14 total parameters were carried out by single factor and interaction factor investigation through design of experiment (DOE) analysis. Total number of 128 experiments was conducted based on 2k factorial design. This large search space poses a challenge for both human experts and machine learning algorithms in achieving the objectives of the industry to reduce the cost of manufacturing by enabling the off hand prediction of laser cut quality and further increase the production rate and quality.

2. Introduction

Reliability and predictability of quality is most important in the choice of precision manufacturing, particularly with the ever increasing move towards "unmanned" machining operations due to the rapid automation of manufacturing industry. The ability to predict, both accurately and effectively, the surface quality during a machining operation will ultimately improve the machining of engineering components, thus reducing significantly the huge machining cost, which can sometimes be as high as 70% of the overall manufacturing cost due to the rework activities (Ezugwu et al., 1995). Recent research activities in artificial neural network (ANN) have shown that ANN has powerful pattern classification and pattern recognition capabilities. ANNs are well suited for problems whose solutions require knowledge that is difficult to specify but for which there are enough data or observations. They learn from examples (training data) and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe. ANN is universal functional approximator (Kuo, 1998). It has been proven that properly designed network can approximate any continuous function to any desired accuracy by many researchers. One has presented wear prediction of polymer-matrix composites, where the ANN was used to calculate the experimental database for short fiber reinforced polymide 4.6 composites, the specific wear rate, frictional coefficient and also some other mechanical properties (Jiang, 2007) . Wilkinson, P. et al. represented an application of an artificial neural network to classify tool wear states in face milling. The input features were derived from measurements of acoustic emission during machining and topography of the machined surfaces. Five input features were applied to the back-propagating neural network to predict a wear state of light, medium or heavy wear (Wilkinson et al., 1999). Neural network capability in developing a reliable method to predict flank wear during a turning process with the input numeric of tool geometry, depth of cut, cutting speed, federate, workpiece properties, cutting fluid (Lee et al., 1996). The cutting force model for self-propelled rotary tool (SPRT) cutting force prediction using artificial neural networks (ANN) has been described in detail. The inputs to the model consist of cutting velocity, feed rate, depth of cut and tool inclination angle, while the outputs are composed of thrust force F_x, radial force F_y and main cutting force, F_z (Hao et al., 2006). The presentation of how to develop a robust approach for prediction of residual stress profile in hard turning for different combinations of material properties, cutting tool geometries and cutting conditions has been carried out (Umbrello et al., 2007). An optoelectronic sensor system has been used in conjunction with a multilayered neural network to predict the flank wear of the cutting tool without interrupting the machining process (Choudhury et al., 1999). Comparison between several architectures of the multi-layer feed-forward neural network with a back propagation training algorithm for tool condition monitoring (TCM) of twist drill wear has also been carried out (Abu-Mahfouz, 2003). Modelling of overcut with neural network analysis for electrochemical surface grinding (ECG) processes. 72 tests were carried out and a back-propagation neural network was trained using the first replicate of the experimental data set. Then, the trained network was tested to be well behaved (Ilhan & Akbay, 1994). A trained multi-layer perceptron to predict spot-weld quality from electrical process data has been presented. This work has centred on the spot-welding and weld-welding of aluminium alloys. Electrical data was sampled in real-time during the spot welding process and the data was processed off-line to extract up to 270 features from each weld. In this case, a multi-layer perceptron, MLP was used to predict output for unseen inputs (Osman et al., 1994).

3. Artificial Neural Network

In this research, the ANN model design follows a stepwise method, progressively adding and comparing possible inputs to output to develop the model. A neural network model

was selected for this work over other techniques because of its ability to model non-linear system, robustness to noisy data, and generic modeling capability. The ANN models in this research were developed, trained, and tested with the Intelligent Neural System to an optimized and satisfactory level of correlation and R-square values before selecting the network for final prediction. Inputs to the neural networks were the numeric of significant parameters which affects the quality of the machining surface. To make the process more accurate and consistent, modeling & simulation is the powerful tool besides experimental exploration of; gas pressure, cutting speed, focal distance (FD), stand of distance (SOD), laser power, frequency and duty cycle. In this prediction modeling, the observed numerical of extreme empirical investigations was used. Since the prediction of the cut quality is our primary aim, the ANN models were initially optimized based on training and testing over all the observed data sets. This methodology was adopted in large scale to ensure the results are met to the satisfactory level of the sponsored industry.
The complete experimental data of 128 sets has been used to train the network. The learning process was stopped after 500 iterations. The number of neurons and layers are calculated automatically based on the network training error based on QBPA algorithm with 7-13-1 architecture. The first step of the calculation is to normalize all the raw input data to values between 3 and 40 as shown in the equation (1).

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

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,

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

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,

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

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.

$$Izi = \sum_{i=1}^{M} w_{xz} x_i + \sum_{i=1}^{N} w_{yz} y_i \tag{4}$$

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.

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

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

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

Where, T_i is the ith 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

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

Where, the L is number of neurons in the output layer.

4. Methodology

Critical consideration has been taken in designing the methodology of the entire research work. After a detail discussion and investigation with machining experts of the industry together with statistical consideration, the seven most-significant parameters were considered as design parameters in developing the model. The critical methodology of the entire research is shown in figure 1.

5. Laser Machining

Laser beams are used extensively for a variety of material-removal applications because they provide highly concentrated energy sources that can be easily transmitted and manipulated. Micro-mechanical structures are becoming more common with the ever increasing demand for new micro-fabrication tools. As feature sizes become smaller and smaller, i.e. typically below 100 µm, conventional mechanical approaches to cutting, drilling and shaping materials may be replaced with photon or particle beam techniques that enable geometric features as small as laser wavelengths (smaller than a micrometer) to be created with a high degree of precision and repeatability. In addition, laser fabrication processes are non-contact, dry, and clean operations that enable ease of automation (Jimin et al., 2007). The nonlinear behavior of the laser-material interactions plays a significant role in forming the final surface profile and the resultant geometry of the machined micro-features. The need to precisely control a large number of parameters, often with random components, makes the task of improving the process performance very difficult (Basem et al., 2002).

Moreover, modeling all these factors using conventional, analytical and numerical methods poses a substantial challenge. In practice, the operator has to perform a number of experiments to set the appropriate process control parameters related to the laser apparatus, motion control system, and workpiece material. This trial-and-error approach is costly and time consuming especially for a small batch production or prototyping, and does not ensure near optimality with a given set of process conditions and manufacturing objectives. Laser cutting is used in precision industries as it has the ability to cut complex profiles featuring extra ordinary shapes, corners, slots, and holes with high degree of repeatability and small region of heat affected zone (HAZ).

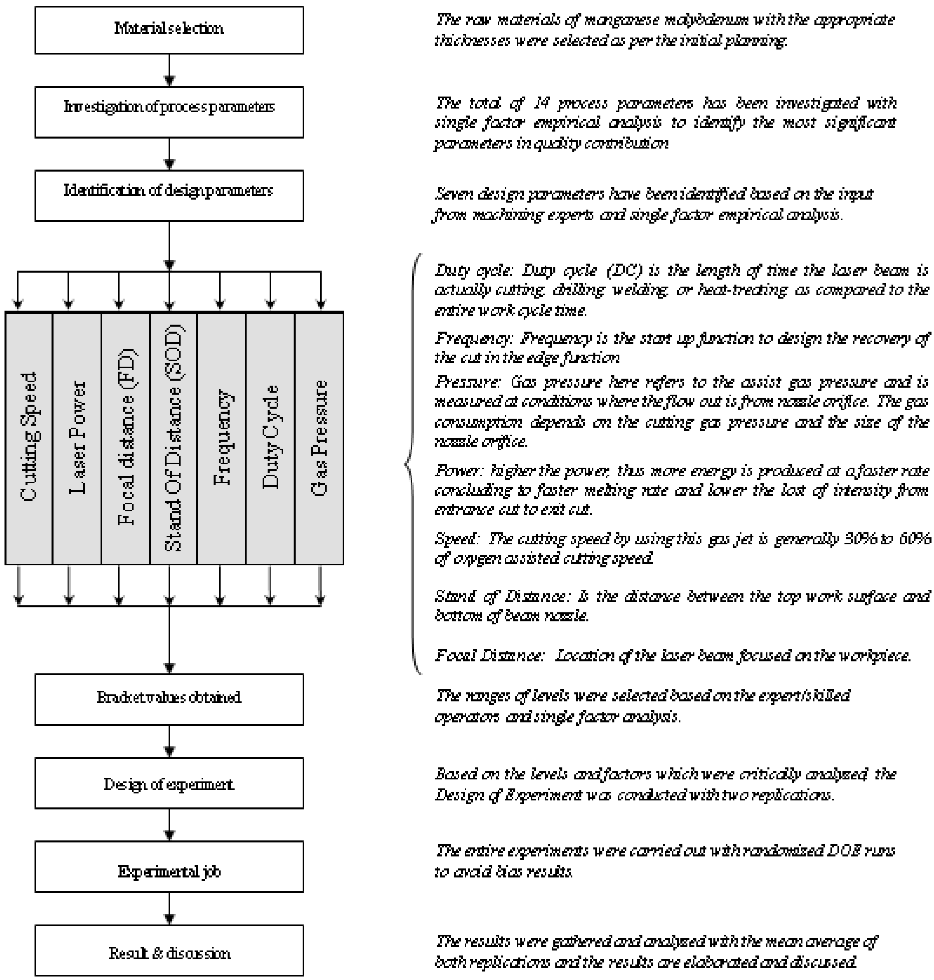

Fig. 1. Research methodology

In laser machining, surface roughness is one of the most important quality evaluation factors. The surface roughness is generally dependent upon the properties of the work material being cut, workpiece thickness, focal length, stand of distance, gas pressure, cutting speed, etc. including the type of cutting gas. Besides the investigation of CO_2 laser cutting parameters investigations are also being studied to further understand the relationship between the gas and the cutting parameters to obtain a good cutting quality.

6. Experimental Setup and Procedure

This scientific investigation is an industry sponsored project in which the kerf width is to be predicted by ANN model to reduce the manufacturing cost and further increase the quality of the end product. In this experiment, seven input parameters were controlled, namely; stand off distance, focal distance, gas pressure, power, cutting speed, frequency and duty cycle. A nozzle diameter of 0.5 mm was used with focused beam diameter of 0.25 mm. Material used in this experiment is grade B, Manganese-Molybdenum pressure vessel plate, with a nominal gauge thickness of 5.0 mm and Tensile Strength of 690 MPa. The plate was cut to the dimension about 1.2 meter length and 0.7 meter width. A cut length of 20mm performed over all the 128 profiles on the plate. Total of 128 experiments have been conducted based on the DOE matrix. All the experimental data sets and the objective function have been trained to develop a sound predictive model. A schematic view of laser machining experimental setup is shown in figure 2.

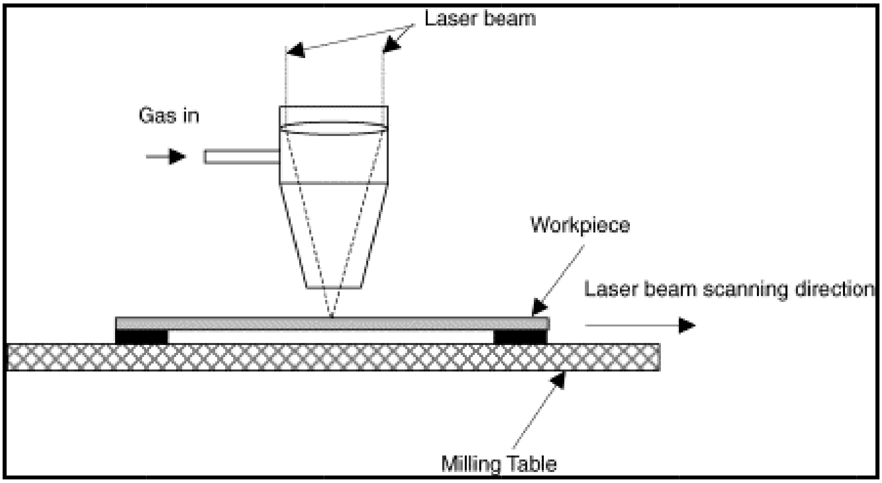

Fig. 2. Schematic of laser machining

7. Experimental Parameters, Machines and Equipments

The workpiece materials, design parameters, laser machine type and its capability together with the entire equipments / apparatus used in this research activity are listed on coming pages. The standards used in data collection and interpretation also stated.

Work Material:
- DIN 17155 HII standard
- 5mm Manganese-Molybdenum
- Grade: B
- Tensile Strength: 550-690 MPa

Controllable parameters:

Variables	Level	
	Low	High
Power (Watt)	2500	2800
Cutting speed (mm/min)	800	1200
Frequency (Hz)	800	1000
S.O.D (mm)	1	1.5
F.D (mm)	0	1
Pressure (Bar)	0.7	1
Duty Cycle (%)	40	80

Laser machine:
- Model: Helius Hybrid 2514 CO2 Laser Cutting Machine
- Controller: FANUC Series 160 i-L
- Maximum capacity: 4 kW
- Laser source that use to create laser beam is CO2 gas. The real ingredient is mixture of N2 (55%), He (40%) & CO2 (5%) with purity 99.995%.
- Pressure = Max 3 bar

Surf tester:
- Mitutoyo Surftest SJ301
- Sampling length range (0.8 ~ 8)

Data collection and interpretations:
- All the experimental materials, procedures, data collections, analysis, etc. are conducted as per the standard recommendations of 'Laser Cutting of Metallic Materials' German Standard, DIN 2310-5.

- The DIN EN ISO 9013:2000 is referred as it gives the terminological definitions and describes criteria for evaluating the quality of cutting surfaces, quality classifications and dimensional tolerances. It applies in the case of laser beam cuts from material thickness of between 0.5mm and 40mm.

8. Result and Discussion

A quick back-propagation algorithm was employed for a multi-layered perceptron. This has several advantages over the standard BP in that it is much faster in terms of rate of learning and has the ability of adjusting the learning rate and momentum term automatically. Seven input nodes (corresponding to power, speed, pressure, focal distance, stand of distance, frequency, duty cycle) and single output node (corresponding to surface roughness) were used. The best ANN architecture was selected based on the heuristic search and the selected intuitively based on the best fitness value (6.804306) with test error of 0.1469 as shown in table 1 which were developed based on the data live training line as shown in figure 3. The best developed 7-13-1 architecture with single hidden layer is shown in figure 4. The entire data sets was trained and tested based on the Dither Randomization approach. The Quick back propagation coefficient was 1.75 with the learning rate of 0.1 for 500 iterations. The output error method was based on sum-of-square and for the output activation was logistic. The training was done with the speed of 834, 999 967 itr/sec. In precise, the result shown by the network can be considered as very much promising with the prediction error below 0.5%. From the network output, it was found of capable to predict the results of the 128 real experiments to its most accurately possible. The plot of comparative signatures (figure 5) of the trained and tested data show clearly the strength of the developed model in predicting the surface roughness for 5mm Mn-Mo plate by laser cutting. The numeric summary of these results is presented by Table 2, which indicates the network strength by means of statistical analysis, R-square and their respective correlation 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

Table 1. The summarized data, which were used to support the architecture selection

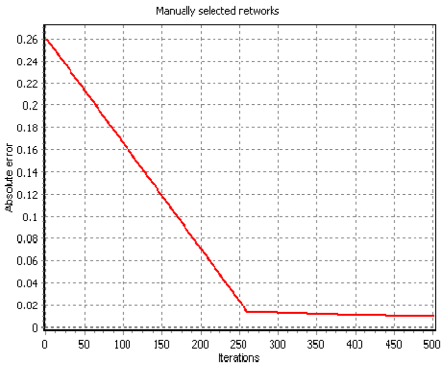

Fig. 3. Iteration vs. error characterization aritecture

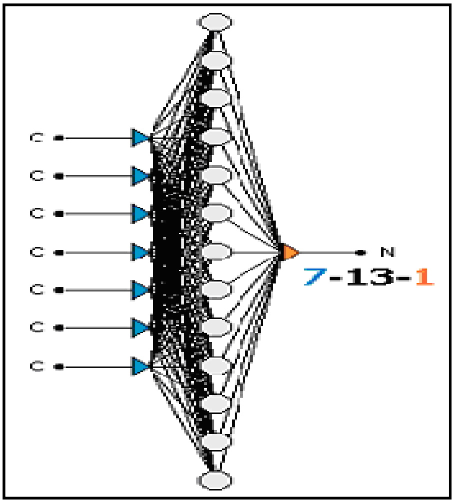

Fig. 4. The 7-13-1 architecture with 7 inputs, 1 hidden layer and singleton output

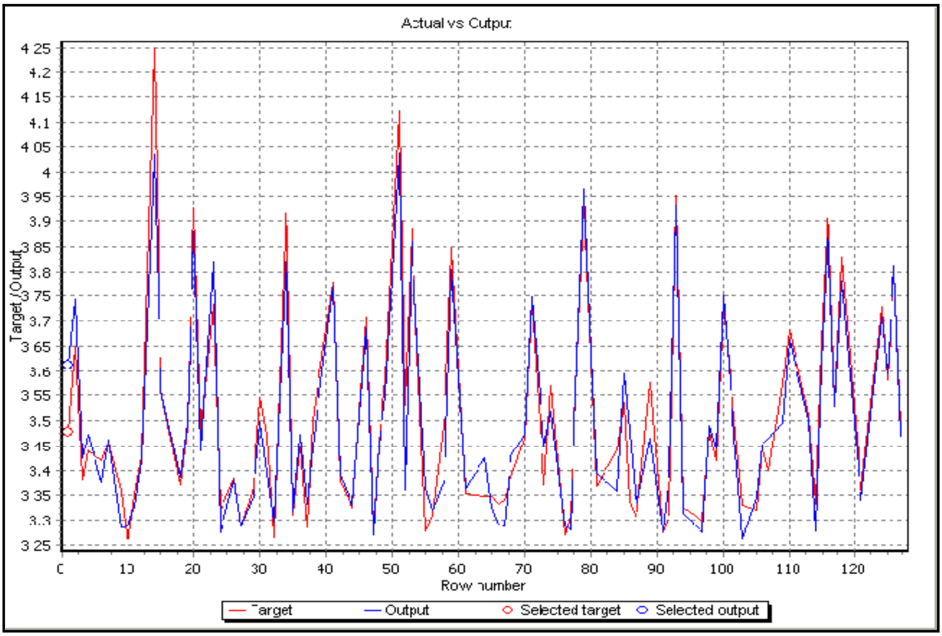

Fig. 5. The comparative signatures of the surface roughness

Summary	Target	Output	AE	ARE
Mean:	3.505181	3.496861	0.041733	0.011796
Std Dev:	0.214885	0.200711	0.039975	0.010916
Min:	3.25	3.263643	0.00067	0.000194
Max:	4.25	4.037391	0.216329	0.050901

Correlation: 0.964416
R-squared: 0.917101

Table 2. Summary of the ANN modeling – Model strength numeric

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