Optimization of CO_2 Laser Cutting Parameters using Adaptive Neuro-Fuzzy Inference System (ANFIS)

Renann G. Baldovino[1], Ira C. Valenzuela[2], Argel A. Bandala[2], Elmer P. Dadios[1]
[1]*Manufacturing Engineering and Management (MEM) Department*
[2]*Electronics and Communications Engineering (ECE) Department*
De La Salle University, 2401 Taft Avenue, 0922 Manila, Philippines

***Abstract*—Laser cutting is a manufacturing technology that uses laser light to cut almost any materials. This type of cutting technology has been applied in many industrial applications. Problems seen with a laser is the cutting efficiency and the quality wherein these two parameters are both affected by the laser power and its process speed. This study presents the modelling and simulation of an intelligent system for predicting and optimising the process parameters of CO_2 laser cutting. The developed model was trained and tested using actual data gathered from actual laser cut runs. For the system parameters, two inputs were used: the type of material used and the material thickness (mm). For the desired response, the output is the process speed or cutting rate (mm/min). Adaptive neuro-fuzzy inference system (ANFIS) was the tool used to model the optimisation cutting process. Moreover, grid partition (GP) and subtractive clustering were both used in designing the fuzzy inference system (FIS). Among the training models used, GP Gaussian bell membership function (Gbellmf) provided the highest performance with an accuracy of 99.66%.**

***Index Terms*—ANFIS; Fuzzy Logic; Laser Cutting; Process Optimization.**

I. INTRODUCTION

Laser cutting operation is an industrial technology that uses a high-power laser beam for cutting both ferrous and non-ferrous materials. However, it was only in the mid-1960s when the first laser machine was applied in large manufacturing processes. Then, after the development of the laser cutting process, the application of laser-assisted oxygen jet cutting in metals with the help of numerical control (NC) technology was first introduced in 1967. The application of laser cutting continued to flourish even in the aerospace industries where it became very useful in cutting titanium of structural airframes that require high precision and accuracy [1].

The only disadvantage observed with the use of laser cutting is its very high-power consumption compared with other cutting technologies, like milling and routing. Generally, laser cutting efficiency ranges from 5% to 45%. Moreover, the required cutting power of any laser type depended on material type, thickness and desired cutting rate [2][3]. Therefore, this paper aims to present an intelligent approach to optimising the laser cutting parameters, especially in the context of cutting rate or process speed. Furthermore, this study will make use of the 200-W CO_2 laser as the generator source. For the cutting method, 'melt and blow' and 'vaporisation cutting' will be applied for both the ferrous and the non-ferrous materials.

II. CNC LASER CUTTING

In order to produce high quality or high accuracy cut, computer numerical control (CNC) technology was integrated into laser systems (see Figure 1).

Figure 1: Process flow of laser machining operations

As illustrated in Figure 2, this type of operation employs a motion control unit in following a desired g-code toolpath to be cut into the material. This toolpath program was designed, drawn and programmed in a computer using a specialised computer-aided drawing and computer-aided manufacturing (CAD/CAM) software [4][5][6].

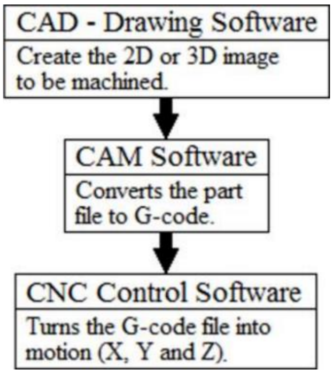

Figure 2: CAD-CAM operation

As mentioned earlier, laser cutting operation mainly involves the use of a highly-focused laser beam and external optics to melt or burn a material. Comparing it with other industrial cutting processes, like plasma cutting and milling, laser cutting leaves the edge with a high-quality surface finish. The primary reason for this is due to the laser generator that produces a near-perfect laser beam quality, which is a requirement for precision cutting. Figure 3 displays an example of a 200-W CO_2 laser generator, manufactured by Synrad.

Figure 3. Synrad Firestar f201 laser

There are three main types of laser cutting: carbon dioxide (CO_2), neodymium (Nd) and neodymium yttrium-aluminium-garnet (Nd-YAG). Among the three types, CO_2 lasers are most common in the industry since it can cut various materials like plastics and steel [7]. Table 1 and 2 provide the amount of heat input requirement and cutting rates for various workpiece materials at different thicknesses, using a CO_2 laser generator source.

Table 1
Heat Input Requirement (watts) of Various Materials Using CO_2 Laser Generator Source

Material	Material Thickness (mm)				
	0.51	1.0	2.0	3.2	6.4
Stainless steel	1000	1000	1000	1000	2500
Aluminum	1000	1000	1000	3800	10000
Mild steel	–	400	–	500	–
Titanium	250	210	210	–	–
Plywood	–	–	–	–	650
Boron	–	–	–	3000	–

Table 2
Cutting Rate (mm/min) of Various Material Using CO_2 Laser Generator Source

Material	Material Thickness (mm)				
	0.51	1.0	2.0	3.2	6.4
Stainless steel	2500	1400	825	470	200
Aluminum	2000	900	400	250	100
Mild steel	–	530	470	380	250
Titanium	760	760	250	200	150
Plywood	–	–	–	–	450
Boron	–	–	–	150	150

III. NEURO-FUZZY SYSTEM

Adaptive neuro-fuzzy inference system (ANFIS) is a type of hybrid intelligent system that fills in gaps of fuzzy systems and neural networks (see Figure 4). This system has been used to model both linear and nonlinear relationship of input and output parameters[8].

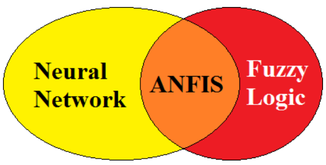

Figure 4: Venn diagram of ANFIS

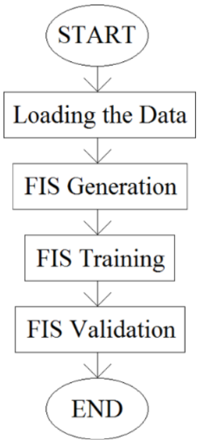

Figure 5: Program flow of ANFIS

ANFIS combines the properties of the fuzzy logic system and neural network. It can process imprecise and vague data and has the capability to learn the network and adapt to the system. It can learn from the inputted training data by clustering them to the same class using the neural network. After training, fuzzy rules will be generated from the trained neural network (see Figure 5). The generation of the rules can be represented through linguistic variables or terms. Moreover, training of the ANFIS model can be performed either by backpropagation or the hybrid learning rule[8]-[11]. The difference between the two models is that the hybrid learning rule combines at least two intelligent technologies.

$$\begin{aligned}
&\text{Rule1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1\text{, then} \\
&f_1 = a_1x + b_1y + c_1 \\
&\text{Rule2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2\text{, then} \\
&f_2 = a_2x + b_2y + c_2
\end{aligned}$$

Figure 6: Sample of FIS using TSK model

Backpropagation process is composed of two phases. The forward phase where the synaptic weight values are initialised and inputs are fed into getting the response. On the other hand, the backward phase makes the error signal propagates in reverse direction to adjust the weighted values. The Sugeno or Takagi-Sugeno-Kang (TSK) method [12] is one of the most common FIS (see Figure 6).

IV. METHODOLOGY

A. *Data Collection and Fuzzification*

The training and testing data used in the experiment were from actual CO_2 laser cut run using four different workpiece materials, namely mild steel, stainless steel, acrylonitrile butadiene styrene (ABS) and acrylic plastic. In every run, the process speed or cutting rate (mm/min) was recorded. Figure 4 shows the observed response of cutting rate in mm/min versus the material thickness in mm for the two plastic materials: ABS and acrylic.

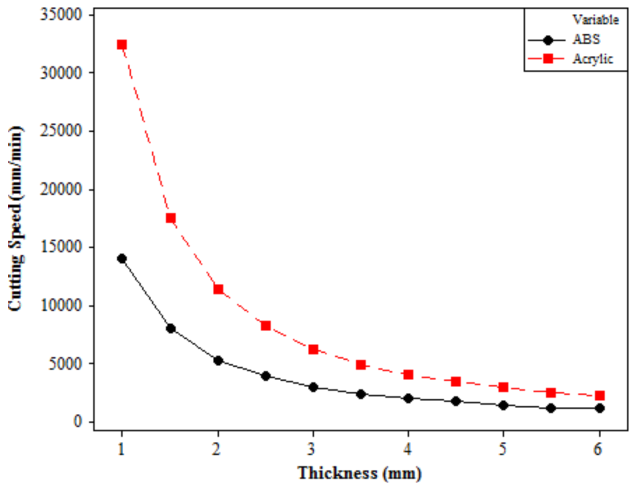

Figure 7: Cutting rate of two plastics in various thickness

On the other hand, Figure 8 displays the response of cutting rate versus the material thickness for the two metals: MS and SS.

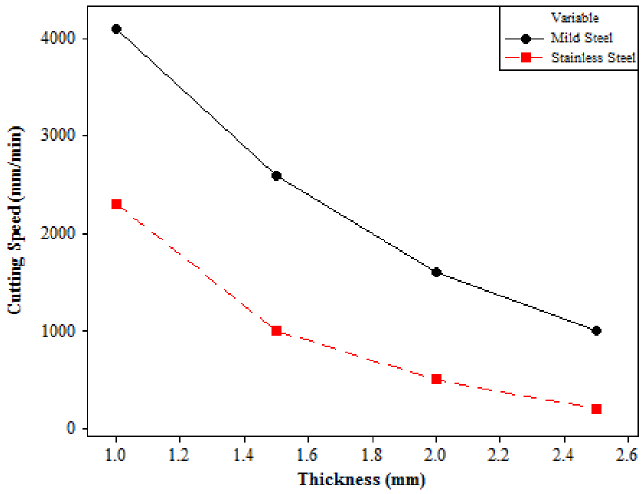

Figure 8: Cutting rate of two metals in various thickness

After the collection of data, the training and testing data were fuzzified by the network generating the FIS model. Different membership functions were used, and the performance of each model was compared.

B. Training of the Neuro-fuzzy Network

To train the system, different FIS algorithms were used. However, before FIS training, the initial model structure was first conducted in MATLAB adaptive neuro-fuzzy inference systems (ANFIS). The neural network was trained using the hybrid learning rule in generating the FIS for the laser cutting optimisation.

The hybrid rule in MATLAB ANFIS is composed both of a forward and a backward pass propagation. In the forward pass, an output and error value is obtained by feeding the input into the network. Meanwhile, for the backward pass, the error and the gradient are propagated from the output to the input to adjust the weights for each network node.

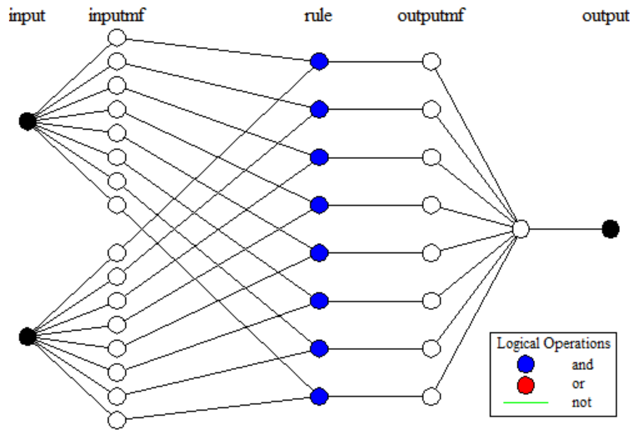

Figure 9: Structure of the ANFIS model network

C. Evaluation of Fuzzy Rules

After training the data, fuzzy rules from the neural network was extracted, and the neuro-fuzzy inference system was tested using data outside the ones used for the training.

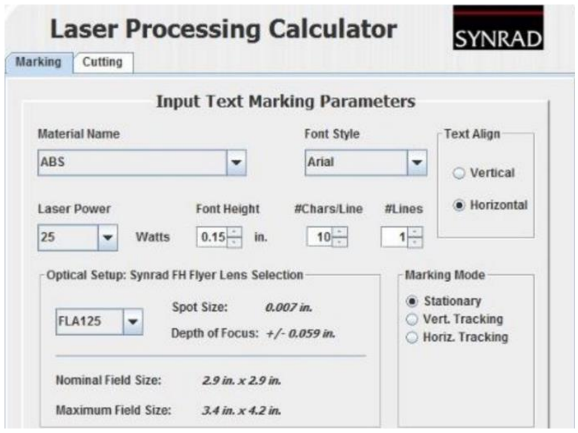

Figure 10: Synrad's laser processing calculator

The performance of the best FIS was measured regarding the error rate or system accuracy against the output from the testing data. In verifying the experimental results, the test data were compared from Synrad's Laser Processing Calculator [13] (see Figure 10).

V. RESULTS AND DISCUSSION

Table 3 displays the correlation performance of each FIS type. GP stands for the grid partition where it is used to form a partition by dividing the input space into several fuzzy slices. Subtractive clustering (SC), on the other hand, is a fast, one-pass algorithm for estimating the number of clusters and their centres in a set of data. In ANFIS, the GP fuzzy system has five memberships for the two inputs. As shown in Table 2, the GP Gaussian bell membership function (Gbellmf) was observed to have the lowest training error of 0.34%, and the highest was seen for the triangular (trimf) and trapezoidal membership functions (trapmf) with an error of 6.4125% and 7.4536%, respectively.

Table 3
Correlation of Training Parameters

Run	FIS Type	Fuzzy Rules	Training Error (%)
1	GP trimf	8	6.4125
2	GP trapmf	8	7.4536
3	GP Gbellmf	8	0.34004
4	GP Gaussmf	8	0.57056
5	GP Gauss2mf	8	0.57294
6	GP pimf	8	7.4536
7	GP dsigmf	8	1.4134
8	GP psigmf	8	1.4134
9	SC	8	1.4134

To further synthesise and understand the behaviour of the fuzzy response, the simulation of the rule evaluation (see Figure 11) was conducted using the MATLAB Simulink program.

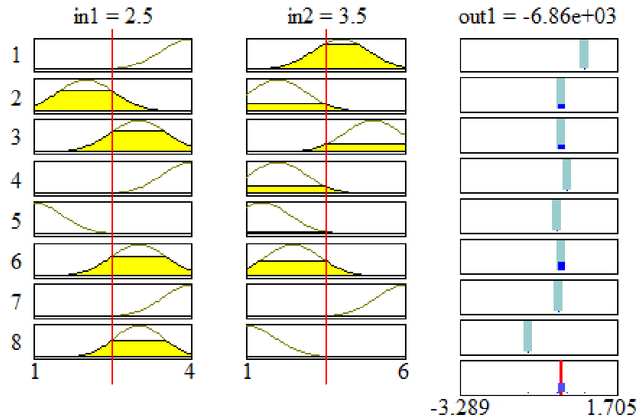

Figure 11: Generated rule viewer from the ANFIS network

The testing of the system was performed by matching the response produced by actual CO_2 laser generator with the FIS output (see Figure 12). To compare with actual data, the laser processing from Synrad was used as a reference. With this, it allows the user to evaluate the feasibility of laser cutting operations. This program is employed with better predictive algorithms and visual feedback for different types of material from plastics to metals.

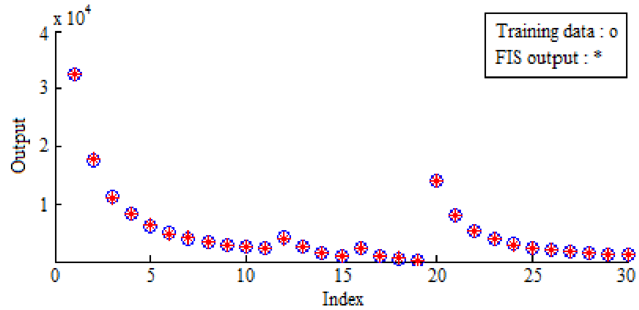

Figure 12: ANFIS results with training data and FIS output

Figure 13 displays the 3D surface or control plot of the generated fuzzy output versus the two inputs: type of material (in1) and thickness (in2). With this kind of plot, it is easy to predict the behaviour of the output. Another advantage of the 3D plot is that it is helpful in conducting fuzzy optimisation runs in the future.

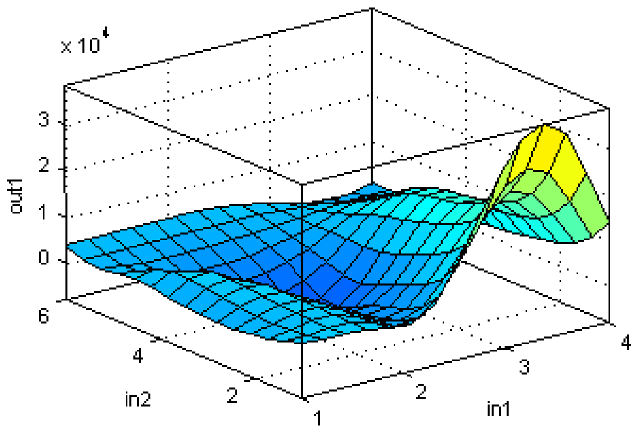

Figure 13: 3D surface plot using GP Gbellmf

VI. Conclusion

In this study, ANFIS was successfully implemented in developing a prediction model for the laser cutting profile parameters on different materials. Among the different FIS models used, it was observed that ANFIS-GP performed slightly better than the ANFIS-SC model, and among the GP, Gbellmf was seen to have the highest accuracy. The prediction model was verified with the test data, where the average error was only 0.34%. The technique used to train the network was the hybrid optimisation since it combines both the least-squares and backpropagation gradient descent method. To verify the results of the experiment, the test data used were compared from actual Synrad's Laser Processing Calculator.

This optimisation model can be applied not only on CO2 laser type but also in Nd-YAG laser. Furthermore, this model can be adopted by other precision cutting machine operations like milling and routing.

References

[1] S. Tarnovean, R. Breaz, C. Biris, O. Bologa, Simulation tools for studying the behavior of CNC laser cutting machines in different working regimes. *2012 16th International Conference on System Theory, Control and Computing (ICSTCC)*, pp. 1-6, (2012).

[2] L. Chiang, J. Ramos. CNC control of a laser cutting machine. *IEEE International Symposium Industrial Electronics (ISIE)*, pp. 236-241 (1994). doi:10.1109/isie.1994.333112.

[3] B. Radu-Eugen, T. Sorin, B. Cristina, B. Octavian-Constantin,. Improving the dynamic behavior and working accuracy of the CNC laser cutting machines. *12th International Conference on Control Automation Robotics & Vision (ICARCV)* (2012). doi:10.1109/icarcv.2012.6485437.

[4] J. Rogelio and R. Baldovino. A PC-based controller for the computer numerically-controlled (CNC) LASER machine. *Lecture Notes in Engineering and Computer Science 1*, pp. 242-247 (2015).

[5] P. da Rocha, R. Diogne de Silva e Souza and M. de Lima Tostes. Prototype CNC machine design. *9th IEEE/IAS International Conference on Industry Applications (INDUSCON)* (2010).

[6] C. Yao, J. Rogelio, R. Baldovino and F. Caluyo. A fuzzy-pulse width modulation (PWM) control algorithm for a computer numerical control (CNC) LASER machine. *Advanced on Mechanical and Manufacturing Engineering Technology (ADMMET)*, Bandung, Indonesia (2015).

[7] Synrad Firestar f201 from Synrad. Retrieved 14 December 2016 from Synrad Inc.: http://www.synrad.com

[8] M. Hosen, A. Khosravi, S. Nahavandi, L. Sinnott. Prediction interval-based ANFIS controller for nonlinear processes. *International Joint Conference on Neural Networks (IJCNN)* (2016). 10.1109/IJCNN.2016.7727844.

[9] R. Baldovino, E. Dadios. Fuzzy logic control: design of a 'mini' fuzzy associative matrix (FAM) table algorithm in motor speed control. *Proc. of the IEEE Region 10 Conf. (TENCON)*, Macau (2015). doi:10.1109/tencon.2015.7372923.

[10] S. Mesbah, G. Pang. Fuzzy-neural control with application to a heating

system. *Proc. of the 1999 IEEE Int. Symposium on Computer Aided Control System Design*, Hawaii (1999). doi:10.1109/cacsd.1999.808704.
[11] E. Dadios, J. Solis. "Fuzzy-neuro model for intelligent credit risk management". *Intelligent Information Management*, vol. 4, no. 5, pp. 251-260 (2012).
[12] "What is Sugeno-type fuzzy inference?" Retrieved 14 December 2016 from MathWorks website: http://www.mathworks.com.
[13] Synrad Laser Processing Calculator from Synrad. Retrieved 14 December 2016 from Synrad Inc.: http://www.synrad.com.