IOP Conf. Series: Materials Science and Engineering **318** (2018) 012066 doi:10.1088/1757-899X/318/1/012066

Sugeno-Fuzzy Expert System Modeling for Quality Prediction of Non-Contact Machining Process

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Abstract. Modeling can be categorised into four main domains: prediction, optimisation, estimation and calibration. In this paper, the Takagi-Sugeno-Kang (TSK) fuzzy logic method is examined as a prediction modelling method to investigate the taper quality of laser lathing, which seeks to replace traditional lathe machines with 3D laser lathing in order to achieve the desired cylindrical shape of stock materials. Three design parameters were selected: feed rate, cutting speed and depth of cut. A total of twenty-four experiments were conducted with eight sequential runs and replicated three times. The results were found to be 99% of accuracy rate of the TSK fuzzy predictive model, which suggests that the model is a suitable and practical method for non-linear laser lathing process.

1. Introduction

Modelling can be divided into traditional and modern techniques. Traditional techniques include full factorial, response surface methodology, and Taguchi, while modern techniques (also known as artificial intelligence (AI)) include neural network (NN), fuzzy logic (FL) and genetic algorithm (GA). Other predictive modelling methods include tree-based, rule-based, nearest neighbour, logistic regression, graphical method and support vector machine, which were designed to solve two types of predictive modelling [1].

There are two types of fuzzy logic: Mamdani and Sugeno, also known as Takagi–Sugeno-Kang (TSK). The TSK model is one of the most powerful engineering tools for modelling and controlling complex systems [2] and was developed in an effort to create a systematic approach to generating fuzzy rules from a given input–output data set [3, 4]. It was shown that the TSK model yielded a more effective result than other AI method [5] when comparing the condition of tool wear for turning processes. Similarly, excellent results were also discovered in trade-off and practical implementation when using TSK type modelling for surface roughness and cutting force in milling operations [6]. In addition, it was shown that using TSK modelling for the prediction of surface roughness in deep drilling revealed a good relationship between the sets of input variables speed and force [7].

There has been increasing development in the engineering technology available for mechanised industries and a shift from traditional to more modern, non-traditional methods. Laser technology is a growing non-traditional method, capable of application to all types of metal and non-metal material. Laser cutting is a non-contact method using a very narrow heat affected zone and is capable of processing most engineering material with a high degree of precision and accuracy [8, 9]. The most commonly used lasers in industries are Carbon Dioxide (CO2) and Neodymium-Doped Yttrium Aluminium Garnet (Nd:Y3Al5O12).

The accuracy and precision of laser cutting has solved many conventional lathe problems, such as the deflection of the work piece whilst turning cylindrical parts with high length to diameter ratio, which causes undesirable taper on the end product. It has been proven that laser cutting has much better control of the taper on a cylindrical part, making it a more suitable process, as there is no physical contact between the laser beam (virtual tool) and the spinning work.

TSK modelling aims to understand the behaviour and scientific reasoning behind the processing phenomenon, and is therefore viewed as an optimal method in modelling the environment to best predict the response.

2. Experiment details

As to validate the performance of 3D laser lathe using modified 2D flat cutting machine, with a tangential insertion of laser beam and spinning workpiece has been precisely setup on the sacrificial table. The details of CO2 laser machine specification are shown in Table 1, while the experimental setup is shown in Figure 1. Throughout these experimentations, constant and variable processing parameters were identified.

Table 1. CO2 Laser Machine Specification

Machine	Specification
Manufacturer	LVD Company N.V, Belgium
Model	Helius-2513
Brand	LVD Helius
Envelope	2500x1250 mm
Maximum speed	250 mm/s
Maximum laser power	3 kW

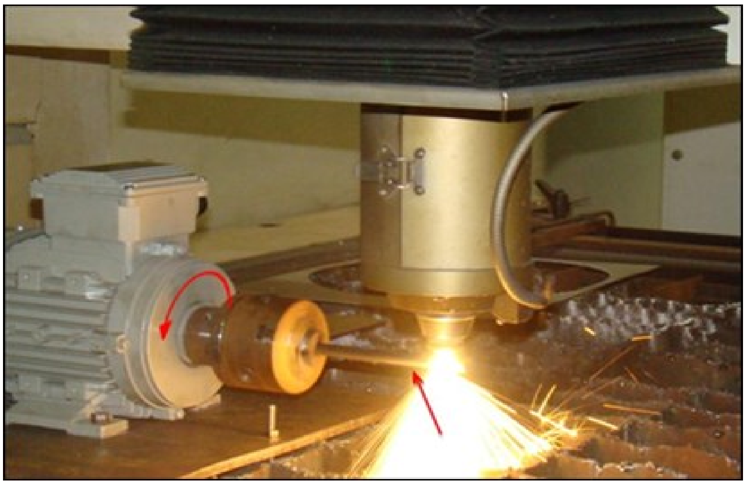

Figure 1. Laser lathing of SS400 steel

Table 2 shows the design parameters namely laser cutting speed (V), work spinning speed (N) and depth of cut (d) which were varied through-out the experiments while Table 3 presents the laser process parameters which were kept constant. Each variable was set into two levels, low and high. The observed responses are tabulated in Table 4.

Table 2. Design parameters

Factors	Levels		
	Unit	**Low**	**High**
Laser cutting Speed (*V*)	mm/min	510	680
Work spinning speed (*N*)	rpm	1000	1500
Depth of Cut (*d*)	mm	1	1.5

The performance of laser machining plays an important role in producing reliable quality measures. Taper is the utmost critical quality to be observed when it comes to the machining of cylindrical parts especially when it is long but small in diameter, which is often called high length to diameter ratio. The taper quality observation of every processed part was made using CNC Formtester MMQ44.

Table 3. Laser process parameters (constant)

Laser Processing	Value
Power	1800 Watt
Frequency	1800 Hz
Duty cycle	85%
Gas pressure	0.5 bar
Laser mode	Continuous wave (CW)
Stand-off distance	1 mm
Nozzle type	Cylindrical
Beam diameter	0.5 mm
Gas jet selection	O2
Focus lens type	Cylindrical
Focal distance	0
Nozzle diameter	1.2 mm

2.1 Sugeno - Fuzzy modelling

Modeling helps to understand the information requirements, minimize time and eliminate cost before starting a real experiment. In this experiment, fuzzy logic was used to model the taper condition of non-linear laser machining environment. Fuzzy logic has become popular over the last decade because it can deal with imprecise inputs, does not need an accurate mathematical model and can handle nonlinearity [10]. Further, fuzzy logic can improve such classifications and decision support models by using fuzzy sets to define overlapping class definitions [11]. By using commercially available Matlab package, Sugeno-Fuzzy inference system was chosen for this study because it’s ideal for acting as an interpolating supervisor of multiple linear controllers that are to be applied, respectively, to different operating conditions of a dynamic nonlinear system [7]. The final output of the system is the weighted average of all rule outputs, and the Sugeno rule operates are shown in Figure 2.

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Table 4. Observed responses

No. Exp.	Machining Parameters			Response
	V (mm/min)	N (rpm)	d (mm)	Taper (mm)
1	510	1000	1	0.040
2			1.5	0.011
3		1500	1	0.011
4			1.5	0.006
5	680	1000	1	0.006
6			1.5	0.005
7		1500	1	0.012
8			1.5	0.005

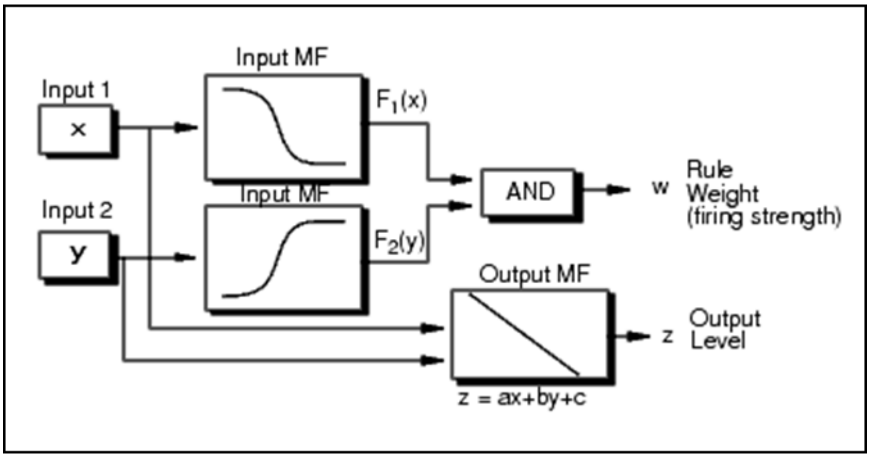

Figure 2. Sugeno final output rule

The main different between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant but can be excellently suited for modeling nonlinear systems by interpolating between multiple linear models [7]. In this experiment, linear membership function has been adopted. Figure 3 shows the output membership function of Sugeno model. The linguistic variables, low and high was used for feed rate, cutting speed and depth of cut to represent the input numerical values. The output numerical values also represent in a similar way. Table 5 shows the fuzzy expressions of input and output parameters in numerical values.

3. Result and discussion

Based on Figure 3, eight rows of rule viewer represent the rules and three columns represent the variable parameters of laser processing. The four plots across the top of Figure 4 represent the antecedent and consequent of the first rule. The defuzzified output represent the aggregate weighted decision for the given inference system. However the decision depends on input values for the system. From the rule viewer, it was witnessed that the optimized values recommended by the Sugeno-Fuzzy are 595 mm/min for feed rate, 1250 rpm for cutting speed, and 1.25 mm for depth of cut.

Table 5. Fuzzy expression of input and output parameters

Rules	IF					THEN
	V	**Connection**	**N**	**Connection**	**d**	**Taper**
1	L	and	L	and	L	ML
2	L	and	L	and	H	L
3	L	and	H	and	L	L
4	L	and	H	and	H	ML
5	H	and	L	and	L	ML
6	H	and	L	and	H	ML
7	H	and	H	and	L	L
8	H	and	H	and	H	ML

*L=Low, H=High, ML=Most Lowest, MH=Most Highest

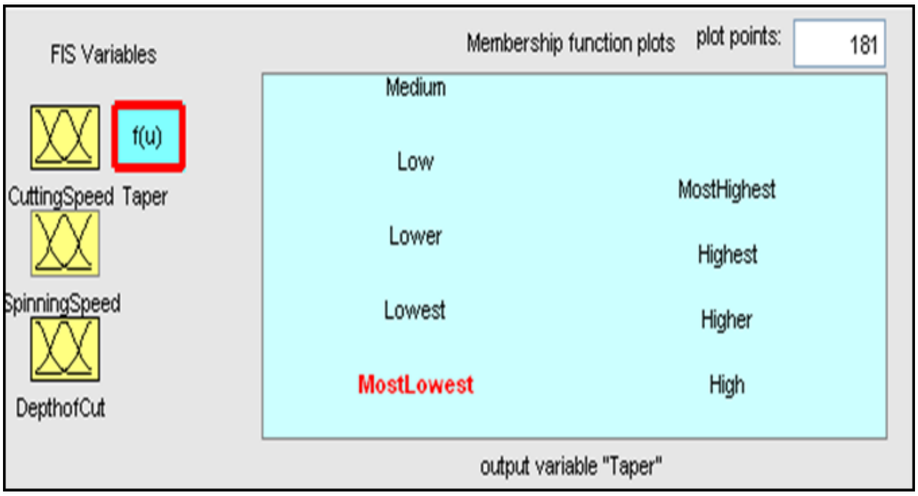

Figure 3. Sugeno output membership function.

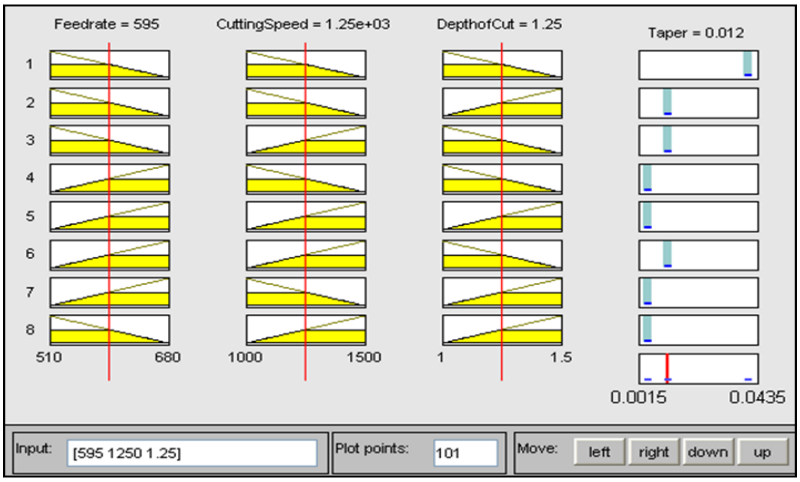

Figure 4. Rule viewer of developed sugeno model.

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On the other hand, the model's estimated response of taper was 0.012 mm. The relationship between prediction and experimental values is shown in Figure 5 which shows excellent correlation among experimental and predicted values where calculated average of percentage error indicates 6.44 percent means it is in the range of acceptable value. Table 6 shows the taper values between experimental and prediction.

Table 6. Taper values experimental vs. prediction

No. Exp.	Exp.	Prediction
1	0.04	0.04
2	0.011	0.012
3	0.011	0.012
4	0.006	0.005
5	0.005	0.005
6	0.012	0.012
7	0.005	0.005
8	0.006	0.005

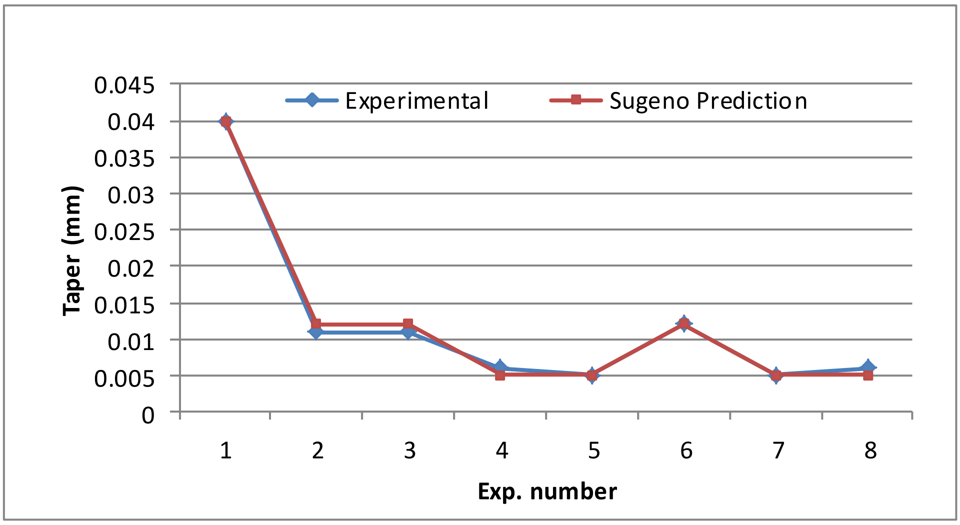

Figure 5. Comparison of prediction and experimental values

With a three-dimensional curve, the interaction between input variable and output response can be seen upon opening the surface viewer. Figure 6 shows the interaction of depth of cut and cutting speed out of taper response while Figure 7 shows the interaction between depth of cut and cutting speed. Via this surface model, it shows that lower spinning speed, cutting speed and depth of cut will increase the taper.

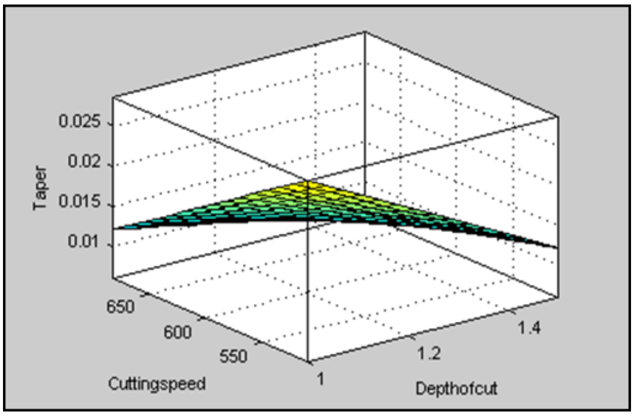

Figure 6. Interaction between depth of cut and cutting speed over taper

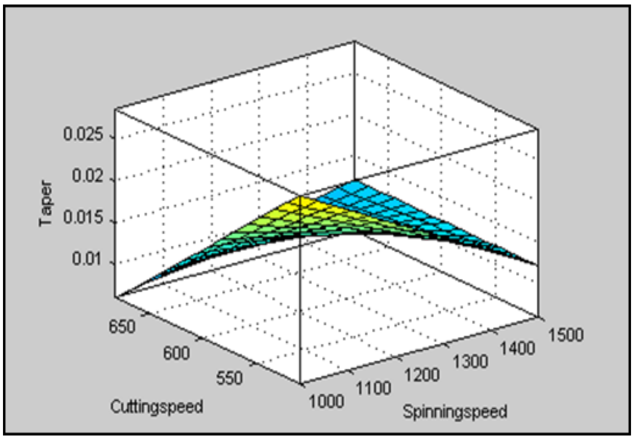

Figure 7. Interaction between depth of cut and spinning speed over taper

4. Conclusion

Prediction of taper has been done successfully and based on the model developed using Fuzzy Logic Tool Box MATLAB (R2013a), taper on the straight turning can be predicted. The results of taper prediction and experimental has been compared and it shows a very good relationship. Sugeno fuzzy model has proved their theory where based on a given input and output data, it shows significant result.

Acknowledgments

First and foremost, the authors would like to thank to Ministry of Higher Education Malaysia for awarding a research grant (Grant #: FRGS/1/2013/TK01/UTEM/03/1) to complete this research. The authors are also in debt to specially thank the top level management of Universiti Teknikal Malaysia Melaka, Centre for Research and Innovation Management, and Faculty of Manufacturing Engineering administrators for their continuous courage and support which brought this research work to a successful finding benefiting industries and mankind. Not forgetting, the LVD (Malaysia) laser technical support namely Mr. Vegiayan Ramiah for his expertise and advice in pioneering this 2D to 3D laser lathing technology.

IOP Conf. Series: Materials Science and Engineering **318** (2018) 012066 doi:10.1088/1757-899X/318/1/012066

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