Design and analysis of hybrid composites using adaptive neuro fuzzy inference system

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Abstract. This article shows an adaptive neuro-fuzzy inference system (ANFIS) model that can predict the cyclic response under a mixture of different parameters. The ANFIS model used for prediction can accurately predict the cyclic reaction of blends with different parameters. It is used for evaluation to predict and analyze the relationship between independent machining variables cutting speed, feed rate, depth of cut and machinability cutting force, cutting power, specific cutting pressure standards. In this evaluation of PEEK CF 30 processed with TiN-coated cutting tools, experiments were conducted and the results obtained were used to apply the ANFIS method to prediction. The primary motive on this research is the affect regarding it factors of cutting force, cutting power and specific cutting pressure.

Keywords: ANFIS, FIS, cutting force, cutting power, specific cutting pressure, cutting speed, feed rate, depth of cut

1. Introduction

Surface roughness plays an essential role in the manufacturing industry, since that perform have an effect on the mechanical properties, cost and exorcism of the product. There are numerous statistical methods that can be used to find the participating parameters, optimize the parameters and estimate the cause in the research work in accordance with the surface roughness by transferring the hybrid contract on the material, without doing a lot about experimental data.

Adel T. Abbas et.al tested then in contrast the experimental data over surface roughness concerning one of a kind cutting parameters among CNC turning operations including regression analysis and ANFIS. Kanhu Charan Nayak et.al proposed that the ANFIS model together with Gaussian number is a predictive tool for milling forces. Djordje cica et.al used ANN, ANFIS models in imitation of check the cutting force, Feed force, and the prediction over the pushed force. The estimated worth do nearly predict the force between the turning operation. Mahdi S. Alajmi et.al proposed a approach because predicting the surface roughness values concerning AISI 304 stainless steel dry then low-temperature the usage of ANFIS-QPSO machine learning method, who perform insure a excessive degree over truth in predicting surface roughness. To determine the degree of association between cutting parameters, cutting force and surface roughness, Ibrahim Maher et.al used the ANFIS model. An ANFIS system has been shown by Ishwer Shivakoti et.al that can use processing parameters such as feed, revolution per minute and cutting depth to predict process response such as material removal rate, surface roughness and cutting force. Vineet Jain et.al revolve around an commentary provision so do makes use of the adaptive neuro-fuzzy inference system (ANFIS) to perceive cutting force based about cutting parameters certain namely spindle speed, feed and depth of cut. C.Kavitha et.al used constants and linear types to take a look at the ANFIS models including special membership function types, and used subtractive clustering according to generate a
fuzzy inference system to predict the surface roughness on the hallosyte nanotubes regarding end-milling concerning aluminium reinforced epoxy hybrid composites. C. Kavitha studied the low prediction oblivion of the bell membership function and other membership functions within ANFIS.

This article considers ternary machining parameters, namely, cutting speed, feed rate and depth of cut. The ranges of these parameters are selected based on preliminary investigations. The research intention establishes a mathematical model of the machining process in order according to uses an ANFIS according to predict machining standards.

2. Methodology

ANFIS was once proposed by means of Jang in 1993, but then Geoffrey Boothroyd et al. proposed that ANFIS is a hybrid of dual technologies, such as adaptive neural network (ANN) and Takagi-Sugeno fuzzy inference system. ANFIS is a technology that focuses on neuro-fuzzy input/output data. The mapping of input parameters below output parameters relating to relevant parameters in a neural network depend on fuzzy logic. The input/output parameter is modified with the aid of the fuzzy technique within the training data. It relies on human information as a fuzzy inference system then generates a single output. Fuzzy technique follows IF–THEN governance to determine the superiority of the membership function. Through back-propagation, gradient descent, least squares method by reducing the sum of square errors, the neural network is used to predict the output, so as to train and then test the input and then output data.

Ishwer Shivakoti et al. regards ANFIS as like comprising on five network layers which are used to perform fuzzy inference systems. Each layer has unique capabilities, for example, Fuzzy layer, Product layer, Normalized layer, Defuzzify layer then Output layer. The layer incorporates couple distinctive nodes, such as square and circle. The square node is an adaptive node that can change the factor, the circle is a fixed factor, and its parameters will change during the training process, and the fixed node is a fixed node. Input nodes are being used by Muhammad Rizal et al. to talk about training values, output nodes talk about expected values and some nodes serve as membership functions and rules in the hidden layer. The present layer’s input is obtained from the nodes in the previous layer. The Sugeno fuzzy inference system’s IF–THEN rules are used as the ANFIS system’s rule base and these rules are fixed as

Rule 1: IF x is A1 AND y is B1, THEN f is f1(x, y)
Rule 2: IF x is A2 AND y is B2, THEN f is f2(x, y),

where the inputs of ANFIS are x and y. Fuzzy sets are A1, B1 and the output of the first order Sugeno fuzzy inference system is f1(x, y) = p1x + q1y + r1, p1, q1, r1 are design parameters that are determined during the training process, f1 is a first order polynomial.

Jang J is used to the characteristics of each layer in ANFIS, as described as below:

Layer 1: The first layer is a layer of fuzzification with in ANFIS network. It is a pre-processing step for information and each node in this layer is adaptive. Converts the numeric input values into fuzzy output values between 0 and 1 with membership functions such as $O_{i,j} = \mu_{A_i}(x_1)$, for node $i = 1, 2$ and $O_{i,j} = \mu_{B_{i,2}}(x_2)$ for node $i = 3, 4$. Here $x_1$ and $x_2$ are the input to node i, $A_i$ and $B_{i,2}$ are fuzzy sets which contain linguistic terms such as small, large etc. $\mu_{A_i}(x_1)$ and $\mu_{B_{i,2}}(x_2)$ are the membership functions.

Various types of membership function have been used such as trapezoidal, triangular, Gaussian etc. Parameters are called introduce parameter.
**Layer 2**: Each node of product layer is a fixed node, which is marked by a circle marked as Π. In addition, it can also perform T-norm operation on the input, but it can also calculates the rule firing strength $w_i$. The output on each rule node is a multiplication concerning membership degrees of the previous layer.

$$O_{2,i} = w_i = \mu_A(x_1)\mu_B(x_2) \quad \text{for } i=1,2$$

**Layer 3**: Each node on normalized layer is fixed nodes, marked by means of a circle is labeled hence N. Each ith node on it layer calculates the ratio about $\bar{r}^th$ node firing strength according to the sum of all rules firing strengths. Output concerning the $\bar{r}^th$ node of this layer is normalized firing strength yet such do stay represented as $O_{3,i} = \bar{w} = \frac{w_i}{w_1 + w_2}$ for $i=1,2$

**Layer 4**: Every node in that layer has adaptive nodes which are called as like defuzzify layer marked through a square yet labeled by way of D. This layer computes the product about normalized firing strength beside previous layer then first order polynomial [sugeno model]. Takagi_sugeno type output of this layer can be represented as $O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x_1 + q_i x_2 + r_i)$ where the evaluation of right hand side polynomials perform consequent parameter set as $\{p_i, q_i, r_i\}$. $\bar{w}_i$ is the normalized weighting factor of the $\bar{r}^th$ rule, $f_i$ is the output of the $i^{th}$ rule of this node.

**Layer 5**: Each node among this output layer has a fixed node, as is separated by using a circle and named afterward it. This wide variety represents the general output as much the sum regarding the membership function and a firing strength yet obtains the genuine estimation about the ANFIS framework.

$$O_{5,j} = \bar{w}_i f_i = \sum_{i} w_i f_i$$

Hybrid learning algorithm use least square technique in conformity with identify the consequent parameters then premise parameters are updated by using gradient descent. If the premise parameters are fixed then the general output can stand expressed as much a linear combination given by the following equation.

$$O_{5,j} = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$

i.e., $O_{5,j} = \bar{w}_1(p_1 x_1 + q_1 x_2 + r_1) + \bar{w}_2(p_2 x_1 + q_2 x_2 + r_2)$

3. Results then Discussion - Prediction concerning the machining of variables through ANFIS access:

In order to prophesy the cutting force, cutting power and specific cutting pressure of PEEK CF 30 processed with TiN coated cutting tools, the technique used is ANFIS. As well as this study, the data were extracted from Issam Hanafi et.al and shown in Table 1. The input parameters are machining parameters certain so cutting speed $v$ (m / min), depth of cut $d$ (mm), feed rate $f$ (mm/rev) and the outputs are the Cutting force $Fm$ (N), Cutting power $Pc$ (W), Specific cutting pressure $Ks$ (N/mm$^2$).

ANFIS is a data learning technology that combines fuzzy logic and neural networks machine learning technology. Fuzzy Logic is used in accordance with transpiration a given input to an platonic output through a membership function. The neural network is weighted in accordance with chart the numerical input in accordance with output to retread the parameters concerning the Fuzzy inference.
system (FIS). Here, the variety of membership functions must be equal to the number of rules. ANFIS is a hybrid algorithm along faster convergence speed, as combines’ gradient descent (backward pass) according to optimize the premise parameters, while the least square method (forward pass) is used to optimize the consequent parameters. The backpropagation algorithm uses a technique called gradient descent to minimize output errors.

In MATLAB toolbox, the graphical user interface neuro-fuzzy designer to solve ANFIS. Initially experiments then simulations are used to acquire input / output data and perform training. The Sugeno-type fuzzy inference system (FIS) is used in accordance with modifies the training data in accordance with the membership function. The membership function regarding the input / output parameters adjustments in the course of learning process is performed through grid partition and sub clustering in the gradient vectors. ANFIS trains a single output system, yet the output membership function need to lie both linear yet constant. Here, the number of output membership functions must stay equalize to the number concerning rules. For each rule the weight is in units of 1, and the weighted average is used to defuzzification. In order to adjust the parameters and reduce some errors by the sum of the squared differences between the actual output and the desired output, the optimization method used is backpropagation algorithm or least squares algorithm. Here backpropagation utilizes whole inputs and output membership functions, however of the hybrid method, the input membership functions are associated along backpropagation, yet the output membership functions are associated with least square estimation. In the ANFIS software, the training step size option can be adjusted, and the data set of the fuzzy inference model can be cross-validated.

Model validation is very beneficial then the information is noisy then overfitting. The error is the root mean square error (RMSE) because of every training epoch. In the structure about the graph, the branches are colour coded, and these branches characterize the characteristics the regulations and point out whether AND, NOT, then OR are used of the rules. In addition, of the structure, the input is represented by means of the left-most node, the output is represented with the aid of the right-most node, and the node represents the normalization aspect about the rule.

In this paper, FIS will create the membership function through the grid partition method, but utilizes optimization technique certain namely back propagation, then mix it with the least square method. The training process has continued until the mandatory training steps (epochs), until the required mandatory root mean square error (RMSE) is reached and the output is produced. If the training process is over, then you can look at the test data which will be used among the identical way to imitate the generalization ability of the adjustment rules and obtain the desired output. The results of the experiment are separated into training and testing. Various types of membership functions are applied to training and test data that help to make better predictions with minimum errors. The results obtained by the experimental work are very close to the predicate output of ANFIS.

The processing parameters in Table 1 and Table 2 such as depth of cut (d), cutting speed (v) and feed rate (f) are used in the training / testing process of the data set.

**Step 1:** To train the data set in table1, the ANFIS model employs a multiple-input single-output structure, which maps the input data through the input membership function and the output data through the output membership function.

**Step 2:** During the learning process, the parameters associated with and membership function are continuously changing, and the rules of a given data set are optimized using a Sugeno-type fuzzy inference system and grid partition technique.

**Step 3:** Hybrid learning methods such as gradient descent and the least square method are employed.

**Step 4:** The input data set is drawn several times to reduce the prediction error in the training process, and the best learning process is used in ANFIS to decrease the error in the parameters. The number of
iterations in the training process is referred to as Epochs and the optimum number of Epochs is calculated through further experiments. This paper includes a total of 27 experiments. The number of iterations needed to determine the optimal number of epoch with the lowest RMSE is 100 epochs.

**Step 5:** With the research data in Table 2, the predictive competence of the corresponding model is verified. After the training process, 9 data sets are checked to validate the model. Table 3, 4 and 5 show how different types of membership functions such as triangular shaped mf, trapezoidal shaped mf, generalized bell shaped mf, gaussian curve mf, pie shaped mf, product of two sigmoidal mf and difference between two sigmoidal mf are used to validate training and testing data parameters to get output in the form of linear, constant using hybrid optimization method. To obtain the best optimal ANFIS structure, the Membership function employs three linguistic variables. Using a hybrid optimization technique for cutting force, triangular shaped membership functions for linear have a lower prediction error than other membership functions i.e. RMSE for testing is 2.8086. Similarly, when using a hybrid optimization method for cutting power, gaussian curve membership functions for linear have a low prediction error when compared to other membership functions. i.e. RMSE for testing is 318.6188 and the hybrid optimization method for specific cutting pressure is a generalized bell shaped membership function for linear, which has a low prediction error compared to the other membership functions, with an RMSE of 148.9239.

Table 1: The data used in this article (Issam Hanafi et.al)

| s.no | cutting speed v (m/min) | Depth of cut d (mm) | Feed rate f (mm/rev) | Cutting force Fm(N) | Cutting power Pc(W) | Specific cutting pressure Ks(N/mm²) |
|------|------------------------|---------------------|----------------------|---------------------|---------------------|----------------------------------|
| 1    | 300                    | 1.5                 | 0.2                  | 165.72              | 49714.92            | 552.39                           |
| 2    | 300                    | 1.5                 | 0.15                 | 143.52              | 43057.42            | 637.89                           |
| 3    | 300                    | 1.5                 | 0.05                 | 98.35               | 29504.73            | 1311.32                          |
| 4    | 300                    | 0.75                | 0.2                  | 111.81              | 33544.34            | 745.43                           |
| 5    | 300                    | 0.75                | 0.15                 | 118.97              | 35689.61            | 1057.47                          |
| 6    | 300                    | 0.75                | 0.05                 | 81.34               | 24402.53            | 2169.11                          |
| 7    | 300                    | 0.25                | 0.2                  | 81.47               | 24439.91            | 1629.33                          |
| 8    | 300                    | 0.25                | 0.15                 | 78.77               | 23631.43            | 2100.57                          |
| 9    | 300                    | 0.25                | 0.05                 | 54.92               | 16475.75            | 4393.53                          |
| 10   | 200                    | 1.5                 | 0.2                  | 204.15              | 40829.95            | 680.5                            |
| 11   | 200                    | 1.5                 | 0.15                 | 186.56              | 37311.21            | 829.14                           |
| 12   | 200                    | 1.5                 | 0.05                 | 129.45              | 25890.87            | 1726.06                          |
| 13   | 200                    | 0.75                | 0.2                  | 151.47              | 30294.15            | 1009.8                           |
| 14   | 200                    | 0.75                | 0.15                 | 136.18              | 27236.58            | 1210.51                          |
| 15   | 200                    | 0.75                | 0.05                 | 92.49               | 18498.29            | 2466.44                          |
| 16   | 200                    | 0.25                | 0.2                  | 96.17               | 19234.9             | 1923.49                          |
| 17   | 200                    | 0.25                | 0.15                 | 87.57               | 17514.22            | 2335.23                          |
| 18   | 200                    | 0.25                | 0.05                 | 62.62               | 12524.38            | 5009.75                          |
| 19   | 100                    | 1.5                 | 0.2                  | 223.2               | 22319.54            | 743.98                           |
| 20   | 100                    | 1.5                 | 0.15                 | 204.4               | 20440.13            | 908.45                           |
| s.no | cutting speed v (m/min) | Depth of cut d (mm) | Feed rate f (mm/rev) | Cutting force Fm(N) | Cutting power Pc(W) | Specific cutting pressure Ks(N/mm²) |
|------|-------------------------|---------------------|----------------------|-------------------|-------------------|-----------------------------|
| 1    | 300                     | 1.5                 | 0.1                  | 125.25            | 37574.18          | 834.98                      |
| 2    | 300                     | 0.75                | 0.1                  | 102.41            | 30721.88          | 1365.42                     |
| 3    | 300                     | 0.25                | 0.1                  | 69.72             | 20916.29          | 2788.84                     |
| 4    | 200                     | 1.5                 | 0.1                  | 164.55            | 32910.07          | 1097                        |
| 5    | 200                     | 0.75                | 0.1                  | 115.94            | 23187.27          | 1545.82                     |
| 6    | 200                     | 0.25                | 0.1                  | 75.34             | 15067.94          | 3013.59                     |
| 7    | 100                     | 1.5                 | 0.1                  | 177.01            | 17700.75          | 1180.05                     |
| 8    | 100                     | 0.75                | 0.1                  | 134.46            | 13446.18          | 1792.82                     |
| 9    | 100                     | 0.25                | 0.1                  | 85.25             | 8524.97           | 3409.99                     |

Table 2: Test data set of ANFIS model

| NO  | No. of Membership function | Function Type | Output Function | Error ( RMSE) |
|-----|---------------------------|---------------|-----------------|---------------|
|     |                           |               |                 | Training Error | Testing Error  |
| 1   | 3 3 3                     | trimf         | constant        | 0.00014539    | 5.3139        |
|     |                           |               | linear          | 0.00021079    | 2.8086        |
| 2   | 3 3 3                     | trapmf        | constant        | 0.00013027    | 12.7762       |
|     |                           |               | linear          | 0.00021965    | 13.6815       |
| 3   | 3 3 3                     | gbellmf       | constant        | 0.00013581    | 6.282         |
|     |                           |               | linear          | 0.00006608    | 6.282         |
| 4   | 3 3 3                     | gaussmf       | constant        | 0.00013894    | 3.2246        |
|     |                           |               | linear          | 0.00085512    | 3.2247        |
| 5   | 3 3 3                     | pimf          | constant        | 0.00013045    | 16.3047       |
|     |                           |               | linear          | 0.000192      | 11.6429       |
| 6   | 3 3 3                     | dsigmf        | constant        | 0.00013055    | 13.1523       |
|     |                           |               | linear          | 0.0014573     | 10.4213       |
| 7   | 3 3 3                     | psigmf        | constant        | 0.00013055    | 13.1523       |

Table 3: Using the hybrid approach, compare the results of different membership functions for cutting force
Table 4: Using the hybrid approach for cutting power, comparing the outcomes of different membership functions.

| NO | No. of Membership function | Function Type | Output Function | Error (RMSE) |
|----|---------------------------|---------------|-----------------|--------------|
|    |                           |               | Training Error  | Testing Error|
| 1  | 3 3 3                     | trimf         | constant        | 0.02879      | 1278.7856    |
|    |                           |               | linear          | 0.055862     | 794.5348     |
| 2  | 3 3 3                     | trapmf        | constant        | 0.025815     | 2670.4651    |
|    |                           |               | linear          | 0.063532     | 2836.1747    |
| 3  | 3 3 3                     | gbellmf       | constant        | 0.027174     | 1377.9669    |
|    |                           |               | linear          | 0.11084      | 1412.3529    |
| 4  | 3 3 3                     | gaussmf       | constant        | 0.027804     | 840.6806     |
|    |                           |               | linear          | 0.18063      | 318.6188     |
| 5  | 3 3 3                     | pimf          | constant        | 0.025854     | 3391.3982    |
|    |                           |               | linear          | 0.069579     | 3028.7553    |
| 6  | 3 3 3                     | dsigmf        | constant        | 0.025874     | 2747.0135    |
|    |                           |               | linear          | 0.33006      | 2746.8676    |
| 7  | 3 3 3                     | psigmf        | constant        | 0.025874     | 2747.0135    |
|    |                           |               | linear          | 0.33091      | 2261.5521    |

Table 5: Using the hybrid approach, comparing the outcomes of various membership functions for a specific cutting pressure.

| NO | No. of Membership function | Function Type | Output Function | Error (RMSE) |
|----|---------------------------|---------------|-----------------|--------------|
|    |                           |               | Training Error  | Testing Error|
| 1  | 3 3 3                     | trimf         | constant        | 0.0020987    | 278.2989     |
|    |                           |               | linear          | 0.005188     | 236.8254     |
| 2  | 3 3 3                     | trapmf        | constant        | 0.002328     | 354.6681     |
|    |                           |               | linear          | 0.010336     | 354.6647     |
| 3  | 3 3 3                     | gbellmf       | constant        | 0.0022469    | 1074.9935    |
|    |                           |               | linear          | 0.016071     | 148.9239     |
| 4  | 3 3 3                     | gaussmf       | constant        | 0.0020059    | 705.7428     |
|    |                           |               | linear          | 0.0073195    | 204.007      |
| 5  | 3 3 3                     | pimf          | constant        | 0.0023283    | 487.9898     |
|    |                           |               | linear          | 0.01046      | 487.9904     |
| 6  | 3 3 3                     | dsigmf        | constant        | 0.0019702    | 246.3691     |
|    |                           |               | linear          | 0.0305       | 344.427      |
| 7  | 3 3 3                     | psigmf        | constant        | 0.0019702    | 246.3691     |
|    |                           |               | linear          | 0.026887     | 365.7466     |

Tables 3, 4 and 5 demonstrate that prediction is possible using fuzzy logic membership functions and an adaptive neuro fuzzy inference system.
4. Conclusion:

The MATLAB toolbox function anfis develops a fuzzy inference system (FIS) from a given input/output data set, with membership function parameters tuned (adjusted) using either a backpropagation algorithm alone or in combination with a least squares method. For the PEEK CF30 machining experiment with TiN coated tools, the ANFIS model was used to predict the cutting force, cutting power and specific cutting pressure. Different types of membership functions, both constant and linear, are used to evaluate the ANFIS model. When comparing the experimental value with the predicted value of ANFIS, it is found that ANFIS is precise. The ANFIS approach is found to be capable of achieving a better experimental value prediction model. In contrast to other models, the ANFIS model is an efficient and effective alternative method.

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