Prediction of Surface Roughness in Milling by Machine Vision Using ANFIS

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ABSTRACT

This paper presents a system for automated, non-contact and flexible prediction of surface roughness of end milled parts through machine vision system which is integrated with an adaptive neuro-fuzzy inference system (ANFIS). The images of milled surface grabbed by the machine vision system could be extracted using the algorithm developed in this work, in the spatial frequency domain using a two-dimensional Fourier transform (2D FT) to get the features of image texture (major peak frequency F_1, principal component magnitude squared value F_2, and the average gray level G_a). Cutting speed(S), feed rate (F), depth of cut (D), G_a, F_1 and F_2 were taken as the input parameters and surface roughness as the output parameter. The results obtained from the ANFIS model was compared with the back propagation (BP) based artificial neural network (ANN). It is found that the error percentage is very close, and it is also observed that the convergence speed for the ANFIS model is higher than the BP-based ANN. The average absolute percentage error for the ANFIS model is 1.68 % and the ANN model is 2.47%. Experimental results have shown that the proposed machine vision system can be implemented for automated prediction of surface roughness with accuracy of 98.32%. The constructed machine vision system is a useful method for measuring the surface roughness with faster, lower price, and lower environment noise in manufacturing process. The results are quite encouraging that the machine vision system can be extended too many real time industrial inspection applications.

Key words: machine vision, surface roughness, ANFIS.
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1 INTRODUCTION

Milling is a widely used machining operation in the manufacturing process. The quality of components produced is of main concern to the manufacturing industry, which normally refers to dimensional accuracy, form and surface finish. Surface roughness of work parts plays an important role on mechanical properties. The proper functioning of a machined part is in many instances largely dependent on the quality of its surface. A precision diamond stylus is drawn through the surface being detected and the perpendicular motion is amplified electronically [31]. Basically surface finish measurement can be divided into two approaches; direct and indirect contact methods. Direct contact depends on using stylus instruments, which require direct contact with surface to be investigated. In this paper, an indirect method using machine vision for inspecting surface roughness in milling has been developed [10]. Machine vision tends to focus on applications, mainly in industry, e.g., vision based autonomous robots and systems for vision based inspection or measurement [13-14].

An automatic manufacturing process that includes aspects of artificial intelligence, such as the capacity to learn and reason, is classified as possessing an advanced level of automation [7][1-3]. Modeling of machining processes has attracted the attention in view of its significant contribution to the overall cost of the product [5]. Developing a CNC milling machine at this level of automation has been an industry goal for many years.

In recent years, many optical measuring methods have been applied to overcome the limitations of stylus method in measuring the surface roughness of work parts. Ho S.Y. et al. used an adaptive neuro-fuzzy inference system (ANFIS) and machine vision system to predict surface roughness in turning. The machine vision system, comprising a digital camera connected to a PC and the appropriate light sources, provided surface images that were analyzed to calculate the arithmetic average of gray levels (number of shades of gray). This information was given for a total of four inputs to the ANFIS and the roughness value could then be obtained [11]. Lo S.P. investigated the possibility and effectiveness of predicting surface roughness with ANFIS. Three milling parameters were selected in his study and compared differences regarding the accuracy rate of the surface roughness prediction [18]. Risbood et al. studied the prediction of surface roughness and dimensional deviation by measuring the cutting force and vibrations in the turning process. In their work, surface finish could be predicted with a reasonable degree of accuracy by taking the acceleration of radial vibration of the tool holder as a feedback [27]. Pal and Chakraborty predicted surface roughness by taking main cutting force, feed force, cutting speed, feed, and depth of cut as input parameters of the network. It was observed that the model with cutting forces as additional input yielded better results [20]. Yamaguchi I et al and Dhanasekaran B et al evaluated the surface roughness using image processing based on mono-chromatic speckle correlation technique [32][6]. Reddy and Rao used genetic algorithm to optimize tool geometry, viz., radial rake angle and nose radius and cutting conditions, viz., cutting speed and feed rate to obtain desired surface quality in dry end milling process [26]. Basak et al. used RBF models to predict surface roughness in finish hard turning process of AISI D2 cold rolled steel with mixed ceramic tools. For better modeling of an RBF network, assistance of multiple-linear regression was taken. Authors observed that in RBF neural network training, the spread parameter, which is essentially the zone of influence of a neuron, plays a significant role. Authors have proposed a strategy for the optimal selection of this parameter [4]. Quiza et al. carried out an experimental investigation on tool wear prediction on ceramic cutting tools used for turning hardened cold rolled tool steel. They predicted tool wear with the help of neural network and regression models. The neural network model was found superior to the regression model [25]. Kumanan et al. proposed the application of two different hybrid intelligent techniques, ANFIS and radial basis function neural network-fuzzy logic (RBFNN-FL) for the prediction of surface roughness in end milling. They found that the hybrid techniques are to be superior over their respective individual intelligent techniques in terms of computational speed and accuracy for the prediction of Surface roughness [15]. Prakasvudhisarn et al. proposed an approach to determine optimal cutting condition for desired surface roughness in end milling. The approach consists of two parts: machine learning technique called support vector machine to predict surface roughness and particle swarm optimization technique for parameters optimization. The authors found that PSO shows consistent near-optimal solution with little effort [24]. Ho W.H. et al. used an ANFIS with the hybrid Taguchi-genetic learning algorithm (HTGLA) to predict the work piece surface roughness for the end milling process. Their experimental results show that the HTGLA-based ANFIS approach outperforms the ANFIS methods in terms of prediction accuracy [12]. Samantha presented a model for predicting surface roughness in end milling using ANFIS and genetic algorithms (GAs). The machining parameters, namely, the speed, feed, depth of cut and the work piece, tool vibration amplitude were used as inputs to model the work piece surface roughness. His experimental results show the effectiveness of the ANFIS approach in modeling the Surface roughness [28]. Dong et al. proposed a model for predicting surface roughness with ANFIS and leave-one-out cross-validation (LOO-CV) approach. Their comparison results indicate that the ANFIS with LOO-CV approach is an effective approach for prediction of SR in end milling process [22].

The major effort was taken to construct a machine vision system for predicting surface roughness of the machined components automatically using various intelligent models from the previous studies. A differential evolution algorithm (DEA)-based artificial neural network (ANN) has been used for the prediction of surface roughness in turning operations. The results obtained from the DEA-based ANN model were compared with the back propagation (BP)-based ANN. It is found that the error percentage is very close, and it is also observed that the convergence speed for the DEA based ANN is higher than the BP-based ANN [33]. A multi response optimisation method using RSM approach was proposed for a miniaturised tool-based micro turning operations. This study investigated the influence of three micro-turning process parameters, which were cutting speed, feed rate and depth of cut. The response variables were average surface roughness (*Ra*), tool wear ratio (TWR) and metal removal rate (MRR). The developed models were used for multi-response optimisation by desirability function approach to obtain minimum *Ra*, TWR and maximum MRR. Maximum desirability was found to be 86.63%. The optimised values of *Ra*, TWR and MRR were 0.0295 µm, 0.0272; 0.098 mg/min respectively for 1101.94 - rpm cutting speed, 10 - µm/sec feed rate, 0.20 - µm depth of cut. Optimised machining parameters were used in verification experiments, where the responses were found very close to the predicted values [21]. An attempt was made in the area of tool-based micromachining for prediction of quality responses such as *R*a, TWR and MRR through a machine vision system which is integrated with an ANFIS. The images of machined surface grabbed by the machine vision system were extracted using the algorithm developed to get the features of image texture *G*a. An area-based surface characterization technique was presented which applies to the basic light scattering principles used in other optimal optical measurement systems. These principles were applied in a novel fashion which is especially suitable for in-process prediction and control. Cutting speed, feed rate, depth of cut, *G*a were taken as input parameters and *R*a, TWR, MRR as the output parameters. The results obtained from the ANFIS model were compared with experimental values. It is found that the predicted values of the responses are in good agreement with the experimental values [23].

Most of the investigations mentioned above, studied the effect of cutting variables on surface roughness by considering one variable at a time. When previous studies are taken into consideration, it is seen that there are still some problems to be resolved. The models that have been developed for surface roughness must be used in all process types and must contain all the cutting parameters. In this paper we choose to extract features of surface roughness in the spatial frequency domain using the 2D FT. The FT is particularly useful for surfaces in noisy conditions owing to tool wear marks, dust, and dirt. The FT characterizes the surface images in terms of frequency components. Major peak frequency F1, which represents the frequency (or, inversely, the wave length) of the feed marks in the image, generally outperforms other roughness features for roughness assessment. Since F1 is the distance between the major peak and the origin, it is a robust measure to overcome the effect of lighting of the environment. The periodically occurring features such as feed marks and tool marks present in the gray-level image can be easily observed from the principal component magnitude squared value F2.

Artificial Neural network (ANN) is the popular and there are many industrial situations where they can be usefully applied. It is suitable for modeling various manufacturing functions due to this ability to learn complex non-linear and multivariable relationships between process parameters. Applying artificial neural networks (ANN) trained by back-propagation algorithm can recognize surface roughness without stopping the machining operation and with reasonable accuracy.

In this work, one more another intelligent technique model recently developed an adaptive neuro-fuzzy inference system (ANFIS) is used to predict the surface finish in end milling operation. This approach has been applied successfully in many vague and complex problems in literature. The resulting network represented model can effectively predict the process output i.e. surface finish, when the process inputs namely spindle speed, feed rate, depth of cut and grey intensity level of the machined surface are given, due to integration of fuzzy logic and Neural Network. Both fuzzy logic and neural network concepts were developed during the last few years independently to understand human behavior patterns, specially the thinking processes in relation to problem solving. While fuzzy logic uses approximate human reasoning in knowledge-based systems, the neural networks aim at pattern recognition, optimization and decision making. A combination of these two technological innovations delivers the best results. Fuzzy adaptive networks are capable of providing both learning ability and tolerance for imprecision, uncertainty and vagueness. As a result, these systems can utilize linguistic information form of the human expert as well as measured data during modeling.

The experimental input and output that is training data of fuzzy adaptive network are collected from common tool and work material used in manufacturing industry under dry condition and forming the Fuzzy adaptive network model. Finally the proposed model is verified and compared by the use of back propagation (BP) based artificial neural network (ANN) model. The major objective of this work is to investigate the potential of neuro-fuzzy systems in CNC-end milling process.

2 EXTRACTION OF MILLED SURFACE IMAGE FEATURES

In this study we use machine vision to assess the surface roughness of machined parts generated by the milling process. Quantitative measures of surface roughness are extracted in the spatial frequency domain using 2D FT. This approach has desirable properties of noise-immunity, orientation dependency, and enhancement of periodic features. Typical noise processes tend to dramatically alter local spatial variation of intensity while having relatively uniform representation in spatial frequency [8]. Frequency domain features should be less sensitive to noise than spatial domain features. Therefore, in this study authors choose to extract features of surface roughness in the spatial frequency domain using the 2D FT. The FT is particularly useful for surfaces in noisy conditions owing to tool wear marks, dust and dirt. The FT characterises the surface images in terms of frequency components [17]. The 2DFT was chosen to extract features of surface roughness in the spatial frequency domain in that work. The periodically occurring features such as feedmarks and toolmarks present in the grey-level image can be easily observed from the magnitude of the frequency components.

The term image refer to a two-dimensional light intensity function, denoted by g(m,n). Where the values at spatial coordinate's m, n gives the intensity (brightness) of the image at that coordinate. As light is a form of energy, g(m,n) must be non-zero and finite, that is,

$$0 < g\,(m,\,n) < \infty \tag{1}$$

The basic nature of g(m,n) may be characterized by two components: (1) the amount of light incident on the object being viewed and (2) the amount of light reflected by the object. Respectively, they are called the illumination and reflectance components and are denoted by i(m,n); and d(m,n).The function i(m,n) and d(m,n) combine as a product to form g(m,n):

$$g(m,n) = i(m,n)\, d(m,n) \tag{2}$$

The nature of i(m,n) is determined by light source, and d(m,n) is determined by the characteristics of the object.

We call the intensity of a monochrome image 'g' at coordinates (m,n), the gray level 'l' of the image at that point. It is evident that 'l' lies in the range

$$L_{min} \leq l \leq L_{max} \tag{3}$$

Let f(m,n) be the gray level of a pixel at (m,n) in the original image of size N×N pixels centered on the origin. The discrete 2D FT of f(m,n) is given by:

$$F(u,v) = \frac{1}{N}\sum_{m=\frac{-N}{2}}^{\frac{N}{2}-1} \cdot \sum_{n=\frac{-N}{2}}^{\frac{N}{2}-1} . f(m,n)\, e^{-j2\Pi(ux+\frac{vy}{N})} \tag{4}$$

For

u, v=−N/2, −N/2+1, 0, 1…, N/2−1. The FT is generally complex; that is

$$F\,(u,\,v) = R\,(u,\,v) + jI\,(u,\,v) \tag{5}$$

Where R(u,v) and I(u,v) are the real and imaginary components of F(u,v), respectively.

The power spectrum P(u,v) of f(m,n) is defined by:

$$P\,(u,\,v) = |F(u,v)|.^2 = R^2\,(u,\,v) + I^2\,(u,\,v) \tag{6}$$

In this study authors have focused on roughness assessment of milled surfaces. The grabbed Images of different jobs using computer vision system are shown in Fig. 1.

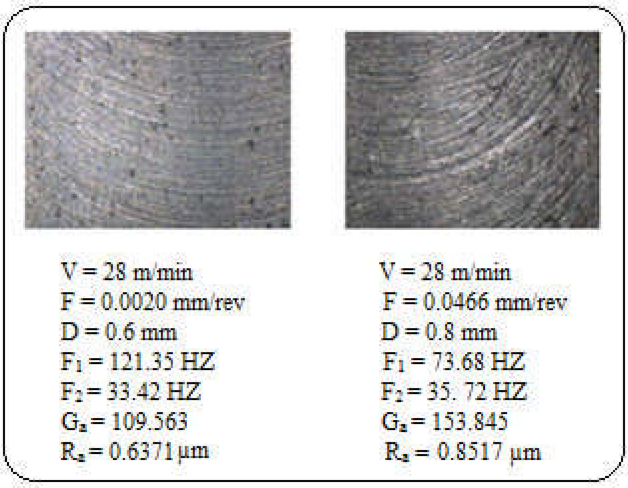

Fig. 1: Grabbed Images of different jobs using computer vision.

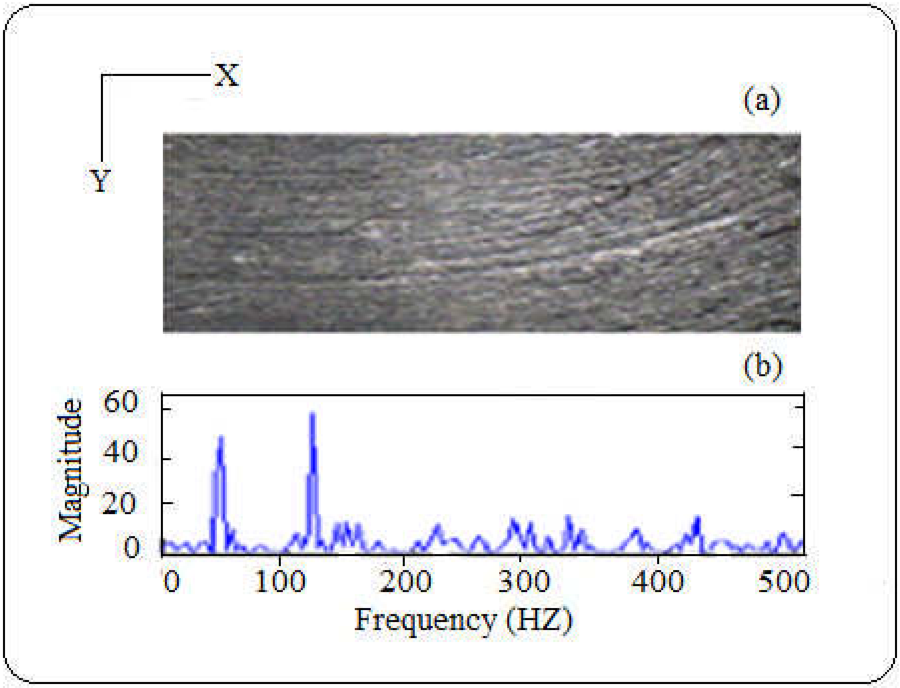

Fig. 2: (a) Milled work piece surface image (b) Major peak frequency.

The features of surface image texture were shown in Fig. 2. Figure 2(a) visually shows the power spectra *P(u,v)* of the surface image as an intensity function, where brightness is proportional to the magnitude of *P(u,v)*. Figure 2(b) present the plot of the power spectrum functions in 2D perspective. It can be seen that the frequency point of the major peak which has the largest magnitude of *P(u,v)*.The distance between adjacent bright spots represents the frequency of the periodic feedmarks in the surface image. A fine machined surface will result in a large distance (i.e. high frequency), and vice versa. We can also observe that the multiple diffuse points around the origin in the power spectrum are generated for milled specimens. These multiple diffuse points correspond to non-periodic features in the original image.

The authors propose 27 roughness features derived in the frequency domain, have been investigated in our experiments. The quantitative definitions of these features are given below. Let

$$P\ (u,\ v) = \frac{P(u,v)}{\sum_{(u,v)\neq(0,0)} P(u,v)} \tag{7}$$

be the normalized power spectrum, which has the characteristics of a probability distribution.

(a) Major peak frequency (F1)

$$F_1 = (u_1^{\ 2}+v_1^{\ 2})^{1/2} \tag{8}$$

Where (u1, v1) are the frequency coordinates of the maximum peak of the power spectrum, i.e.,

$$P\ (u_1,\ v_1) = max\ \{p(u,v), \forall(u,v) \neq (0,0)\} \tag{9}$$

Since the feature F1 is the distance of the major peak (u1, v1) from origin (0, 0) in the frequency plane, it is a robust measure to overcome the effect of lighting of the environment.

(b) Principal component magnitude squared (F_2)

$$F_2 = \lambda_1 \tag{10}$$

Where λ1 is the maximum Eigen value of the covariance matrix of p (u, v); the covariance matrix M is given by:

$$M = \begin{bmatrix} Var(u^2) & Var(uv) \\ Var(uv) & Var(v^2) \end{bmatrix}. \tag{11}$$

For which

$$Var\ (u^2) = \sum_{(u,v)\neq(0,0)}\ [u^2 . p(u,v)] \tag{12}$$

$$Var\ (v^2) = \sum_{(u,v)\neq(0,0)}\ [v^2 . p(u,v)] \tag{13}$$

$$\mathrm{Var}\ (u,\ v) = Var\ (v,\ u) = \sum_{(u,v)\neq(0,0)}\ [uv\ .\ p(u,v)] \tag{14}$$

Features F2 indicate the variance of components along the principal axis in the frequency plane. The eigenvector associated with eigenvalue λ_1 for the covariance matrix of *P(u,v)* indicates the direction of the principal axis in the frequency plane and can be used to estimate the direction of a surface.

(c) Average gray level (Ga)

The captured image is processed in the computer using Matlab Software (version7). The image is digitized into a rectangular array of intensity values. Each array element called ‘pixel’ corresponds to the mean intensity in a small rectangular area of the original image. These values are referred as the gray levels of the corresponding pixels. Each pixel corresponds to a gray intensity level. Ga is the arithmetic average of gray-level intensity values that can be expressed as:

$$G_a = \frac{1}{n}\sum_{i=1}^{n}|G_i| \tag{15}$$

Where G_i is the average gray level of surface image deviated from the mean gray value and n is the number of sampling data.

3 MODELING OF SURFACE ROUGHNESS BASED ON ANN

An ANN is a parallel, distributed information processing structure that mimics the human brain to learn from examples or mistakes [29]. Neural networks, based on their biological counterparts, attempt to model the parallel, distributed nature of processing in the human brain. Since this concept was introduced in 1950s, ANN technology has been adapted in many applications that are complex and non-linear in nature, with an unknown and hard-to-identify algorithm [30]. The mathematical model of an artificial neuron's behavior is the simplification of the biological brain neuron as shown in Fig. 3. A neural network provides a networking structure in which artificial neurons are interconnected as shown in Fig. 4.

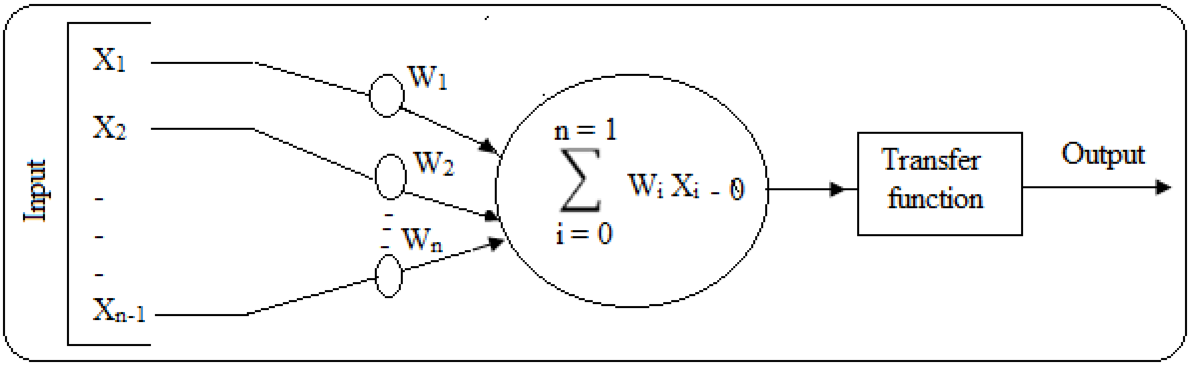

Fig. 3: The behavior of an artificial neuron.

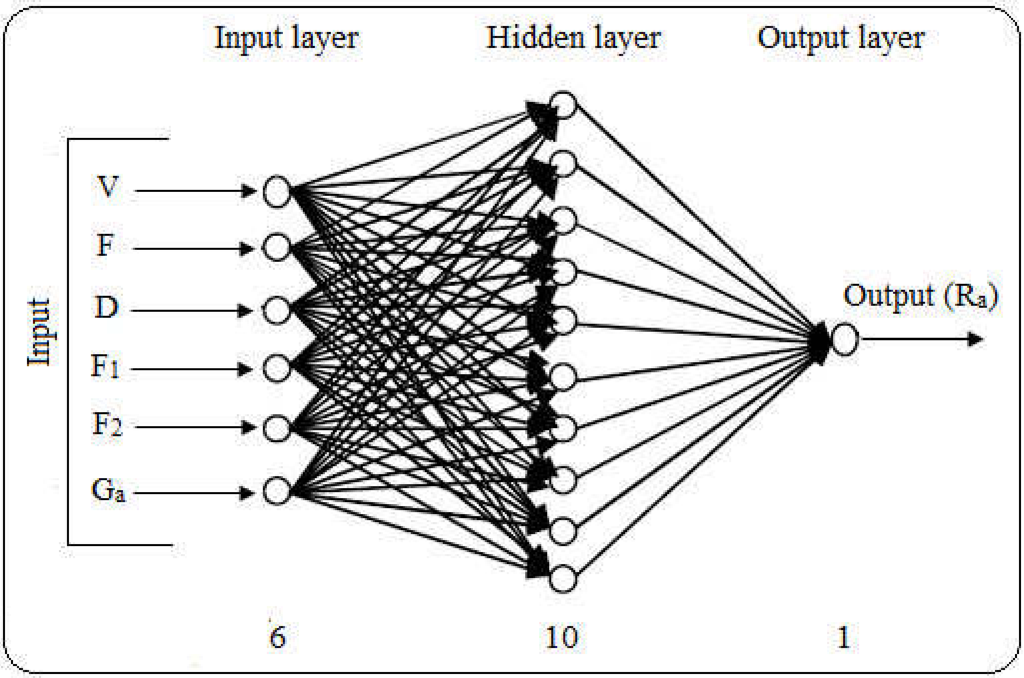

Fig. 4: Structure of the ANN for predicting the surface roughness by vision system.

Various inputs x(n) to the network multiplied by weights w(n) are sent to a neuron. Performing accumulation and threshold, the neuron sums the weighted inputs, passes the result through a non-linear transfer function, and provides an output Yi:

$$Y_i = f\left(\sum_{i=0}^{n-1} w_i x_{i-} \theta\right) \tag{16}$$

where the inputs of xi in this study corresponds to feed rate, spindle speed, depth of cut, and vibration signals; θ is the internal threshold or offset of a neuron; and f is the non-linear transfer function. The most commonly used f is defined by the sigmoid logistic function as:

$$f(x) = \frac{1}{1+e^{-x}} \tag{17}$$

Each neuron in a layer receives weighted inputs from the neurons in the previous layer. The output of the neuron in the previous layer is, in turn, connected as the input to several other neurons in the following layer, which forms a complete network. Beyond the input and output layers, several other

layers of neurons in the middle, called hidden layers, might be needed to build an effective neural network that is capable of solving problems. The principle underlying neural networks is pattern recognition. Among the variety of neural network algorithms, back-propagation (BP) is the most commonly used due to BPs superior strength in pattern recognition and reasonable speed. The training procedure for a back-propagation network is usually iterative and involves a trial-and-error approach that consists of the following steps:
Step 1: Initialize weights and offsets, starting from a small random value.
Step 2: Present inputs and desired outputs to the neural network model.
Step 3: Calculate actual outputs, y_m.
Step 4: Calculate the error between the output from the neural network and the desired output by E

$$E = \frac{1}{nm} \sum_{m \cdot} \sum_{n \cdot} \left(y_{m,n} - d_{m,n}\right).^2 \tag{18}$$

Where m is the number of neurons in the output layer (in this study m=1), and n is the number of training data set. If E is smaller than the required accuracy, then no other learning procedures are needed.
Step 5: If E is larger than the required accuracy, adjust the weights of the networks. The weights are adjusted by:

$$w_{ij}(t+1) = w_{ij}(t) + \eta \delta_j x_i' \tag{19}$$

Where x_i' *is* either the output of neuron *i* or an input, η is a gain term, and δ_j is an error term for neuron *j*.
Step 6: Repeat steps 3–6 until the error of the entire set is less than the required accuracy.

4 INTEGRATION OF FUZZY LOGIC AND NEURAL NETWORK

Neural network and fuzzy logic though different technologies, can be used to accomplish the specification of mathematical relationships among numerous variables in a complex dynamic process, perform mappings with some degree of imprecision in different ways and can be used to control nonlinear systems to an extent not possible with conventional linear control system. Fuzzy modelling [16] has found numerous practical applications in control and prediction. Fuzzy logic is one of the successful applications in the control engineering field which can be used to control various parameters of the real time systems. This logic combined with neural networks yields very significant results. Neural networks can learn from data. However, understanding the knowledge learned by neural networks has been difficult. To be more specific, it is usually difficult to develop an insight about the meaning associated with each neuron and each weight. In contrast, fuzzy rule based models are easy to be understood because it uses linguistic terms and the structure of IF-THEN rules. Unlike neural networks, however, fuzzy logic by itself cannot learn. On more, neural network and fuzzy logic represent two distinct methodologies to deal with uncertainty. Each of them has its own merits and demerits. Neural network can model complex nonlinear relationship and are appropriately suited for classification phenomenon in to predetermine classes. On the other hand, the precision of outputs is quite often limited and does not admit zero. Besides, the training time required for neural network can be substantially large. Also, the training data has to be chosen carefully to cover the entire range over which the different variables are expected to change. Fuzzy logic system address the imprecision of inputs and outputs directly by defining them using fuzzy sets and allow for a greater flexibility in formulating system descriptions at the appropriate level in detail. The learning and identification of fuzzy logic systems need to adopt techniques from other areas, such as statistics, system identification, etc... Since neural networks can learn, it is natural to merge these two techniques. This merged technique of the learning power of the neural networks with the knowledge representation of fuzzy logic has created a new hybrid technique, called as the term ‘ANFIS’. Since ANFIS design starts with a pre-structured system, design of factor for learning is limited, i.e., the membership function of input & output variables contain more information that neural network has to drive from sampled data sets. Knowledge regarding the systems under design can be used right from the start. Part of the system can be excluded from the training. Hence, this ANFIS process is more efficient. The rules are in the linguistic forms and so intermediate results can be analyzed and interpreted easily. The modification of rules is possible during the training and the optimization can be done manually.

ANFISs which are an integration of Neural Network (NN) and Fuzzy Logic system (FS) have demonstrated the potential to extend the technologies when applied individually. Fig. 5(a) Shows the case, where one piece of equipment used the two system for different purpose without mutual cooperation. The model Fig. 5(b) used the neural network (NN) to optimize the parameters of the fuzzy system (FS) by minimizing the error between the output of the FS and given specification or to apply neural network learning capabilities to fuzzy system more adaptive to changing environment.

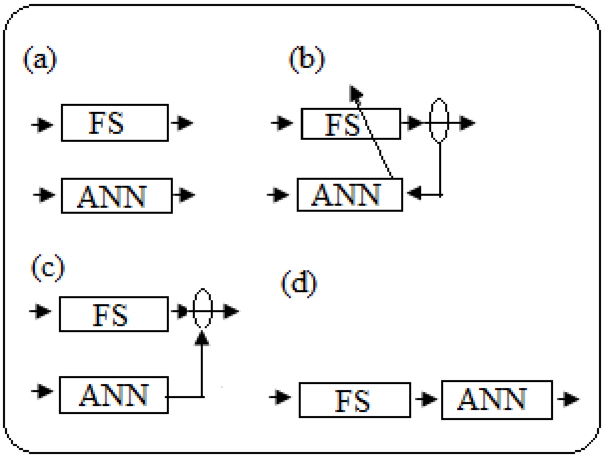

Fig. 5: Integration of ANN and FS.

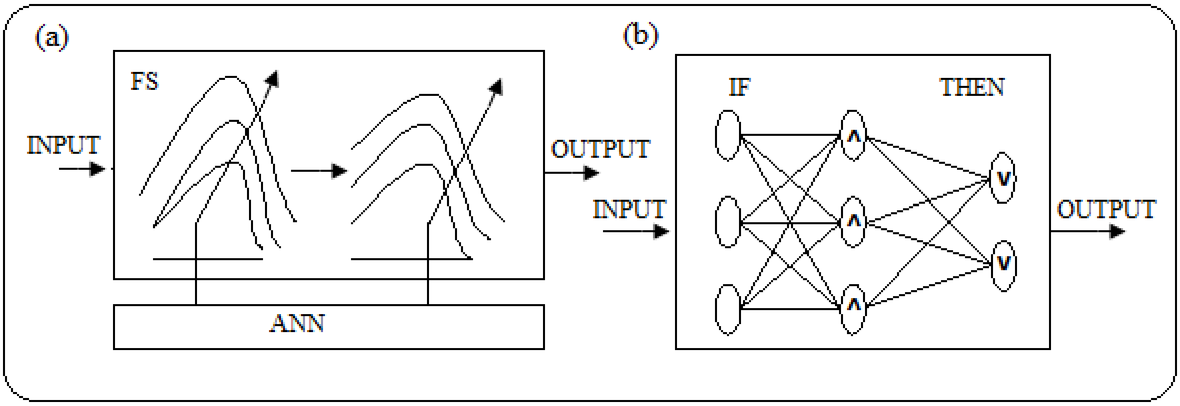

Fig. 6: Combination model with an equal structure.

Fig. 5(c) shows a model where the output of an FS is corrected by the output of an NN to increase the precision the final system output. Fig. 5(d) shows a cascade combination of an FS and NN where the output of an FS or NN becomes the input of another NN or FS. Fig. 5(b) and (c) model refer to a combination model with an equal structure, respectively. These are described details in Fig. 5(a), (b) and Fig. 6(a) show the total system is described by means of fuzzy system, but the membership function of the fuzzy system is produced and adjusted by the learning of neural network The model in Fig. 6(b) shows the fuzzy system can be described by a neural network, the max (V) and min (Λ) operators for fuzzy interface are used to map the relationship between input and output of the Fuzzy Neural Network.

4.1 ANFIS Architecture

ANFIS is a new inference system, in which a universal approximator is introduced to represent highly non-linear functions. ANFIS are fuzzy Sugeno models put in the framework of adaptive systems to facilitate learning and adaptation [19]. Such a framework makes fuzzy system more systematic and less relying on expert knowledge. An ANFIS gives the mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership functions [9]. Both neural network and fuzzy logic are used in ANFIS architecture. Basically, five layers are used to construct this inference system. Each ANFIS layer consists of several nodes described by the node function. The inputs of present layers are obtained from the nodes in the previous layers. Fig. 7 shows the ANFIS structure for a system with m inputs *(X_1…X_m)*, each with *n* membership functions (MFs), a fuzzy rule base of *R* rules and one output *(Y)*.

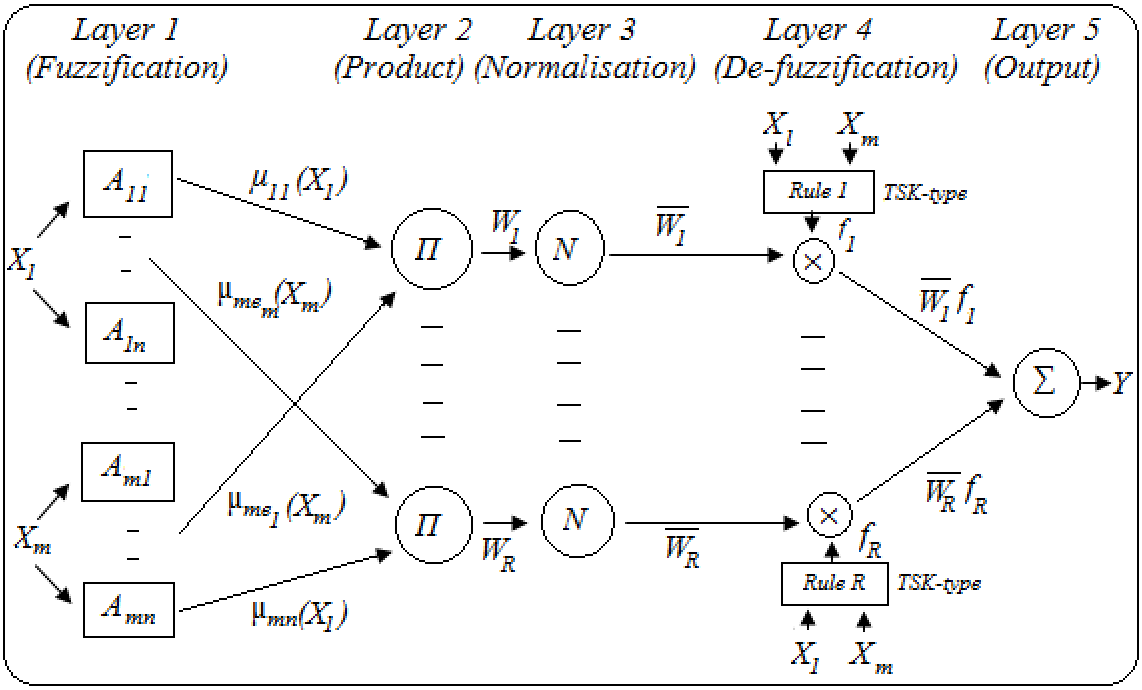

Fig. 7: Basic structure of ANFIS.

The network consisting of five layers is used for training Sugeno-type fuzzy interface system (FIS) through learning and adaptation. Number of nodes *(N)* in layer 1 is the product of numbers of inputs *(m)* and membership functions *(n)* for each input, i.e., *N=mn*. Number of nodes in layers 2-4 is depends on to the number of rules *(R)* in the fuzzy rule base. Five Layers of ANFIS model are as follow:

Layer 1: (Fuzzification layer)

Fuzzification layer transforms the crisp inputs X_i to linguistic labels (*Aij*, like small, medium, large etc.) with a degree of membership. The output of node *ij* is expressed as follows:

$$O^1_{ij} = \mu_{ij}(X_i)_j \qquad i = 1\ldots m, \quad j = 1\ldots n \tag{20}$$

Where μ_{ij} is the j^{th} membership function for the input X_i)

Several types of membership functions are used, for example, triangular, trapezoidal and generalized bell function. In this study it is selected a triangular shape – linear membership by trial and error, as follows:

$$\mu(X) = exp\,(\frac{-(X-C)^2}{2\sigma^2}) \tag{21}$$

The parameters for triangular represent the parameters σ and *c, t*he triangular shaped functions vary while the values of this parameter are changing. These parameters are named as premise parameters.

Layer 2 (Product layer)

For each node *k* in this layer, the output represents weighing factor (firing strength) of the rule *k*. The output *Wk* is the product of all its inputs as follows:

$$O_k^2 = W_k = \mu_{1e_1}(X_1)\ \mu_{2e_2}(X_2)\ ...\ \mu_{me_m}(X_m) \tag{22}$$

$$K = 1...R \quad , \quad e_1, e_2... e_m = 1...n$$

Layer 3 (Normalized layer)

The output of each node *k* in this layer represents the normalized weighing factor *Wk* of the k^{th} rule as follows:

$$O_k^3 = \overline{W}_k = \frac{W_k}{W_1 + W_2 + ... + W_R} \tag{23}$$

Layer 4 (De-fuzzification layer)

Each node of this layer gives a weighed output of the first order TSK-type fuzzy if then rule as follows:

$$O_k^4 = \overline{W}_k f_k \tag{24}$$

Where f_k represents the output of k^{th} TSK-type fuzzy rules as follows:

$$If\ (X_1\ is\ A_{1e_1})\ and\ (X_2\ is\ A_{2e_2})\ and...and\ (X_m\ is\ A_{me_m})$$

$$Then\ f_k = \textstyle\sum_{i=1}^{m} P_{1e_i} X_i + r_k \tag{25}$$

Where P_{ie_i} and r_k are called consequent parameters and $e_1, e_2,...,em=1...n, k=1...R$.

Layer 5 (Output layer)

This single-node layer represents the overall output *(Y)* of the network as the sum of all weighed outputs of the rules:

$$O^5 = Y = \textstyle\sum_{k=1}^{n} \overline{W}_k f_k \tag{26}$$

4.2 Linear-Back-Propagation Learning Algorithm in ANFIS

When the premise parameters are fixed, the overall output is a linear combination of the Consequent parameters. In symbols, the output f can be written as

$$\begin{aligned} f &= \frac{w_1}{w_1+w_2} f_1 + \frac{w_2}{w_1+w_2} f_2 \\ &= \bar{w}_1 f_1 + \bar{w}_2 f_2 \\ &= (\bar{w}_1 x)\ p_1 + (\bar{w}_1\ y)\ q_1 + (\bar{w}_1)\ r_1 + (\bar{w}_2 x)\ p_2 + (\bar{w}_2\ y)\ q_2 + (\bar{w}_2)\ r_2 \end{aligned} \tag{27}$$

This is linear in the consequent parameters$\{p_i, q_i, r_i\}$. A back-propagation algorithm adjusts the consequent parameters in a forward pass and the premise parameters $\{a_i, b_i, c_i\}$ in a backward pass. In the forward pass the network inputs propagate forward until layer 4, where the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backwards and the premise parameters are updated by gradient descent. Because the update rules for the premise and consequent parameters are decoupled in the back-propagation learning rule, a computational speedup may be possible by using variants of the gradient method or other optimization techniques on the premise parameters. Since ANFIS and radial basis function networks are functionally equivalent under some minor conditions a variety of learning methods can be used for both of them.

5 EXPERIMENTATION

Building an ANFIS for a machine vision system can predict the surface roughness under a variation of cutting conditions, a training database need to be established with regard to different cutting parameters and surface roughness. A number of end milling experiments were carried out on a

CNC milling machine. The Machining status in CNC milling as shown in Fig. 8 (variable speed 0.370 kw PMDC, 0 – 4000 rpm) using a high speed steel end mill cutter (6mm) for machining aluminum alloy work pieces. The Rapid 1 Computer vision system for acquiring the images is shown in Fig. 9. The equipment used for measuring surface roughness was a surface roughness tester, Surfcorder SE-1100.

The feasible spaces of the cutting parameters were selected by varying the cutting speed in the range 28-47 m/min, the feed rate in the range 0.002- 0.0466 mm per revolution, the depth of cut in the range 0.6-1.0 mm. The average surface roughness R_a, which is the most widely used surface finish parameter in industry, is selected in this study. It is the arithmetic average of the absolute value of the

Fig. 8: Machining status in CNC milling.

Fig. 9: Rapid 1 Computer vision system for acquiring the images.

heights of roughness irregularities from the mean value measured within the sampling length of 8 mm and measurement speed of 0.5 mm/s. Twenty seven experiments have been conducted for the various sets of cutting conditions i.e. cutting speed, feed rate and depth of cut. The experimental data of end milling operation is shown in Tab. 1.

The surface roughness of the turned work-piece was measured by using SE-1100 portable Surfcorder, within a sampling length of 8mm and with a measurement speed of 0.5 mm/s.

Sl.no.	V m/min	F mm/rev	D mm	F_1 HZ	F_2 HZ	G_a	R_a μm
1	28	0.0020	0.6	121.35	33.42	109.563	0.6371
2	28	0.0020	0.8	88.45	38.84	140.910	0.5705
3	28	0.0020	1.0	102.38	42.76	124.460	0.5039
4	28	0.0333	0.6	60.58	39.24	139.622	0.777
5	28	0.0333	0.8	95.36	41.26	109.787	0.670
6	28	0.0333	1.0	92.86	40.72	110.750	0.644
7	28	0.0466	0.6	51.26	36.52	165.813	0.9183
8	28	0.0466	0.8	73.68	35.72	153.845	0.8517
9	28	0.0466	1.0	107.82	36.21	123.449	0.687
10	38	0.0020	0.6	56.75	39.81	143.451	0.370
11	38	0.0020	0.8	118.93	34.82	117.280	0.3025
12	38	0.0020	1.0	65.38	40.87	138.275	0.2359
13	38	0.0333	0.6	97.62	37.82	125.892	0.5097
14	38	0.0333	0.8	62.65	37.02	150.378	0.4431
15	38	0.0333	1.0	59.86	38.84	145.970	0.3765
16	38	0.0466	0.6	97.59	39.64	111.837	0.6503
17	38	0.0466	0.8	58.88	37.33	144.170	0.5837
18	38	0.0466	1.0	59.24	38.17	144.985	0.587
19	47	0.0020	0.6	72.86	42.26	134.268	0.178
20	47	0.0020	0.8	62.92	40.52	26.100	0.0345
21	47	0.0020	1.0	71.82	41.82	24.210	0.0321
22	47	0.0333	0.6	83.28	40.32	141.670	0.2417
23	47	0.0333	0.8	64.11	39.86	138.334	0.236
24	47	0.0333	1.0	96.34	36.72	81.840	0.1085
25	47	0.0466	0.6	65.68	38.34	148.220	0.3823
26	47	0.0466	0.8	112.38	37.74	122.400	0.3157
27	47	0.0466	1.0	92.60	41.28	128.623	0.286

Tab. 1: Experimental data of End milling operation.

The basic experimental set-up consists of a vision system (CCD camera: Pulnix-TM6, 768_565 pixels, with Image, LC processing hardware with four frame buffers and 1/30 s grabbing speed) and an appropriate lighting arrangement. Illumination of the specimens was accomplished using a diffused white light source, which is kept at an angle of approximately 45^o incidence with respect to the specimen surface on both sides and the intensity of lights same for all tests. The camera is also set up at an angle of approximately 10 $^\circ$ with respect to the normal of the specimen surface, and at a distance of approximately 30 cm from the specimen surface in order to protect the camera from the flowing hot chips. This setting enhances the characteristics of surface patterns, and gives the best quality of surface images.

The images of milled surface grabbed by the machine vision system have been extracted to get the features of image texture (major peak frequency F_1, principal component magnitude squared value F_2, and the average grey level G_a) as the input parameters of the networks generation that classifies surface roughness of parts in a fixed orientation, we allow the specimens to be rotated through minor angles so that precise alignment can be eliminated. Each specimen was rotated between -4 $^\circ$ and 4 $^\circ$ in approximately 1° increments; two images of 512 x 480 pixels were grabbed in each orientation. For each original image of 512 x 480 pixels, the authors selected arbitrarily three distinct sub-images of 256 x 256 pixels as the training samples for networks. The sub-image of size 256 x 256 pixels corresponds to approximately 4.5 x 4.5 mm 2 of a specimen surface. The sampling procedure above was also repeated, but with only one sub image of 256 x 256 pixels in each grabbed image, to generate the required test samples.

A schematic diagram of the computer vision system for measuring surface roughness is shown in Fig.10.

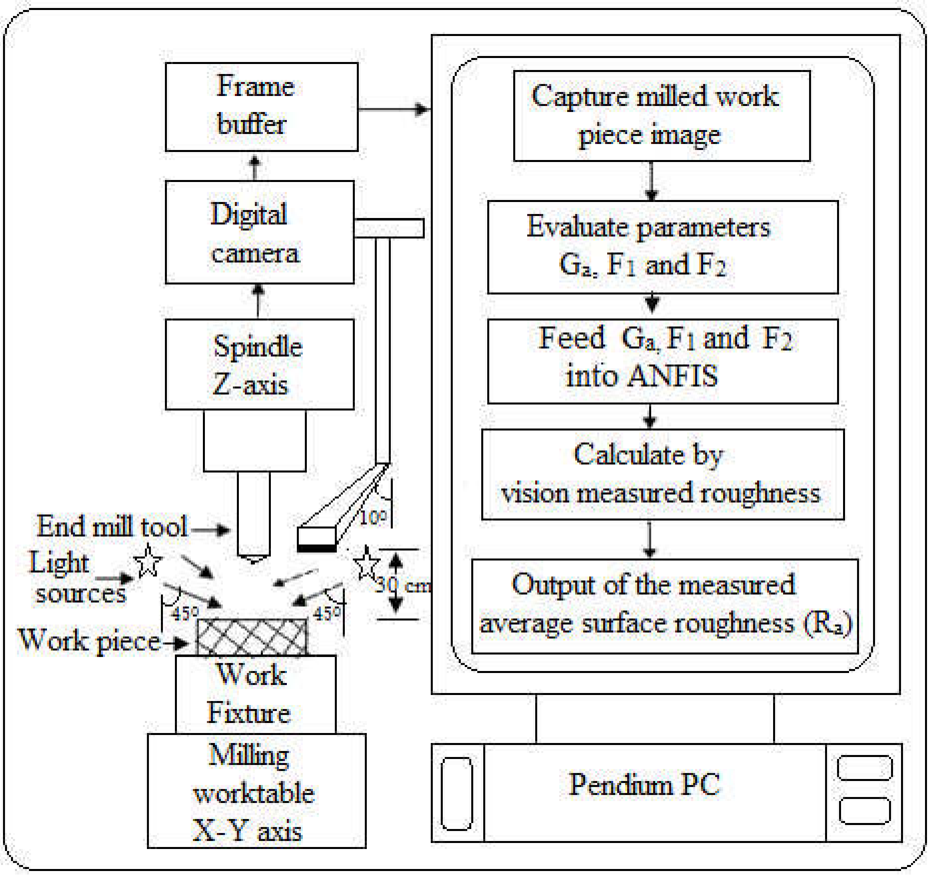

Fig. 10: Schematic diagram of the machine vision system for measuring surface roughness in end milling using ANFIS.

The surface roughness R_a is the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value measured:

$$R_a = \frac{1}{n}\sum_{i=1}^{n}|y_i| \tag{28}$$

Where y_i is the height of roughness irregularities from the mean value and n is the number of sampling data. The cutting speed, feed rate, depth of cut and gray value were taken as input parameters and surface roughness was considered as output response.

5.1 Implementation of Neural Network Trained by BP-Algorithm

In order to assess the ability of the ANFIS model relative to that of neural network, an ANN model was developed using the same input parameters. The neural networks model for the surface roughness prediction was trained in the following training procedure. In the training process, the “trial-and-error” method is employed to determine the number of hidden layers, the neurons in each hidden layer, the learning rate, and the momentum factor in the neural networks model. A few neural networks structures with varied numbers of hidden neurons are compared and the structure of 6 - 10 - 1 that creates the least prediction errors is selected as the system model.

By following the same procedure, the learning rate is set as 1 and the momentum factor is set as 0.5. As a result, the architecture of the ANN model specified as 6 – 10 – 1. The Network architecture 6 - 10 - 1 is shown in Fig. 11.

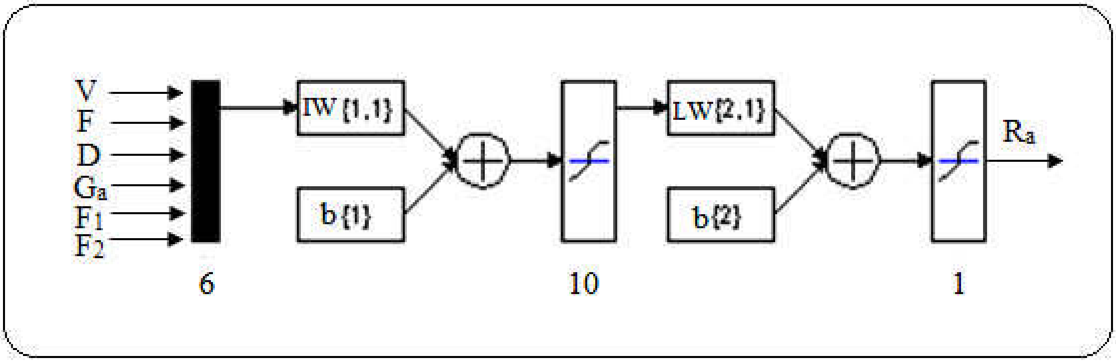

Fig. 11: Network architecture 6-10-1.

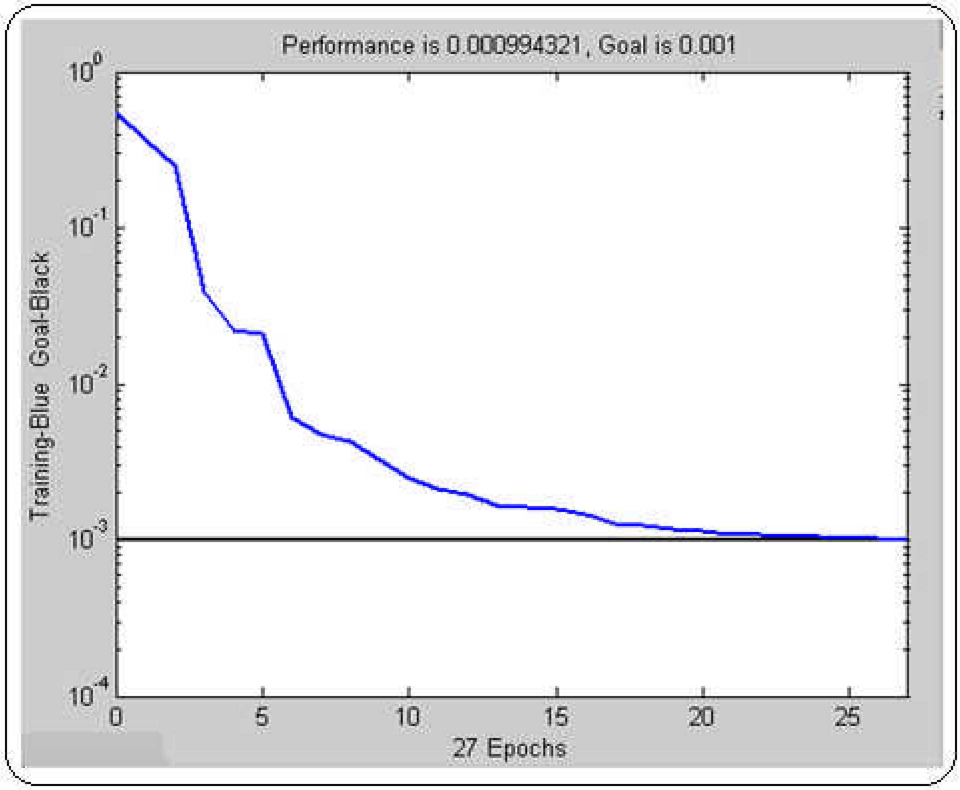

Fig. 12: Performance of Neural network (6 - 10 - 1).

After the training procedure, the weights between each neuron and the bias of each neuron were obtained. The performance of Neural network (6 - 10 - 1) is shown in Fig. 12 depicts the average training error versus iteration number. This network is trained till the error is 0.001. This neural networks model can be used for predicting surface roughness in real time.

5.2 ANFIS Implementation

ANFIS modeling refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modeling. The neuro fuzzy systems have potential to capture the benefits of both the fascinating fields into a single frame work. This system eliminates the basic problem in fuzzy system design (i.e. obtaining a set of fuzzy if-then rules) effective by using the learning capacity of an ANN for automatic fuzzy if-then rules generation. To implement the methodology in ANFIS, each output response, the Gauss - linear membership function is created and the meaningful linguistic statements are selected for each variable and expressed by appropriate fuzzy sets. The Initial membership function plot for the input variable ‘cutting speed’ is shown in Figure 13.

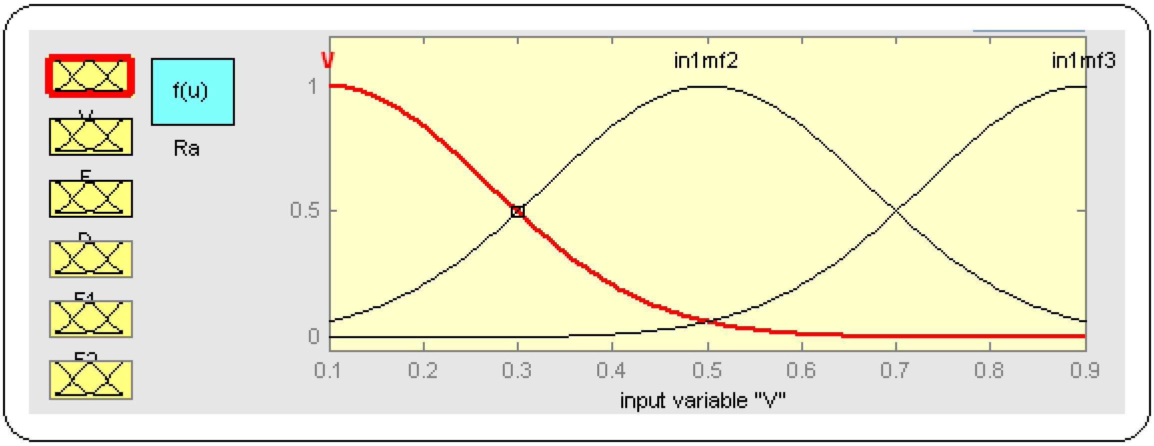

Fig. 13: Initial membership function plot for the input variable ‘cutting speed’.

6 EXPERIMENTAL VERIFICATION AND DISCUSSION

Verifying the developed networks to predict the surface roughness of end milling, 10 more milled specimens using different cutting parameters were performed. As the cutting speed, feed rate, depth of cut and the average gray level is fed into the developed models ANN and ANFIS the surface roughness measured by the vision system can be calculated directly. The Experimental milling parameters and surface roughness for testing the networks were listed in Tab. 2. The Comparison of ANN and ANFIS Predicted values with Experimental values were shown in Tab. 3.

Sl.no.	V m/min	F mm/rev	D mm	F_1 HZ	F_2 HZ	G_a	R_a μm
1	32	0.0120	0.7	50.5200	58.9230	171.8620	0.6633
2	30	0.0220	0.9	41.7300	57.8090	186.2800	0.5543
3	34	0.0320	0.95	41.0780	60.4100	187.8700	0.4391
4	36	0.0400	0.97	66.4000	61.5680	142.3800	0.6358
5	37	0.0380	0.8	71.2650	62.0100	26.4400	0.3971
6	40	0.0420	0.98	83.4700	63.9200	140.4800	0.8164
7	42	0.0360	0.85	92.0460	65.0910	129.8600	0.7866
8	44	0.0280	0.75	100.6100	66.2600	128.6800	0.8153
9	45	0.0180	0.65	104.9900	66.8200	116.9200	0.6633
10	46	0.0450	0.90	108.6760	67.2980	121.7900	0.6774

Tab. 2: Experimental milling parameters and surface roughness for testing the networks.

Sl.no.	R_a µm (Experimental)	R_a µm (ANN-Prediction)	R_a µm (ANFIS-Prediction)	Absolute % of error (ANN)	Absolute % of error (ANFIS)
1	0.6633	0.6753	0.6618	1.5	0.23
2	0.5543	0.5718	0.5513	3.15	0.54
3	0.4391	0.4266	0.4346	2.83	1.02
4	0.6358	0.6523	0.6361	2.59	0.05
5	0.3971	0.4191	0.3853	5.5	2.97
6	0.8164	0.8274	0.8179	1.34	0.18
7	0.7866	0.7751	0.6988	1.07	11.16
8	0.8153	0.8298	0.8169	1.77	0.20
9	0.6633	0.6443	0.6644	2.86	0.17
10	0.6774	0.6919	0.6758	2.14	0.24
			Average absolute % error	2.47	1.68
			Predictional accuracy	97.53	98.32

Tab. 3: Comparison of ANN and ANFIS Predicted values with Experimental values.

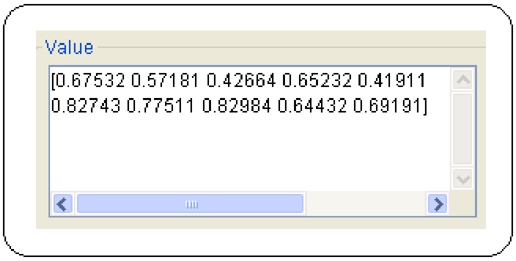

Fig. 14: Testing output for ANN-BP - trained network – surface roughness.

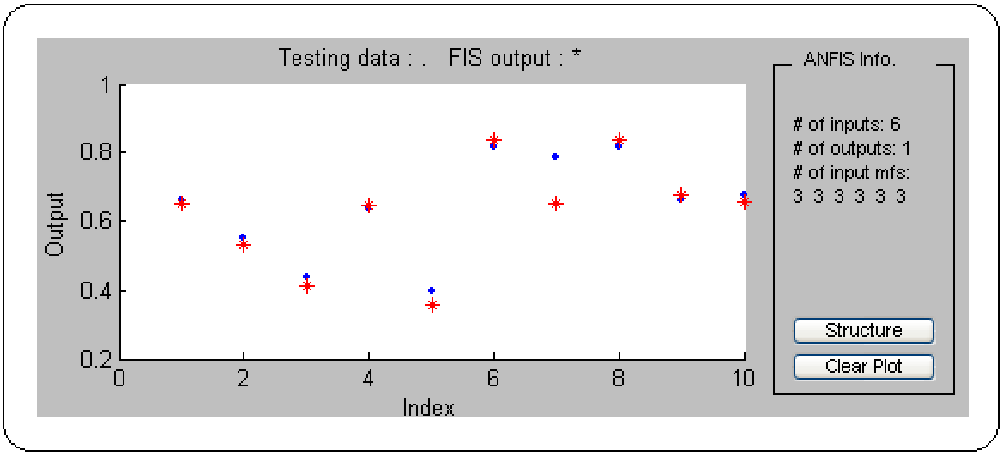

Fig. 15: Output performance of ANFIS based on triangular - linear membership function.

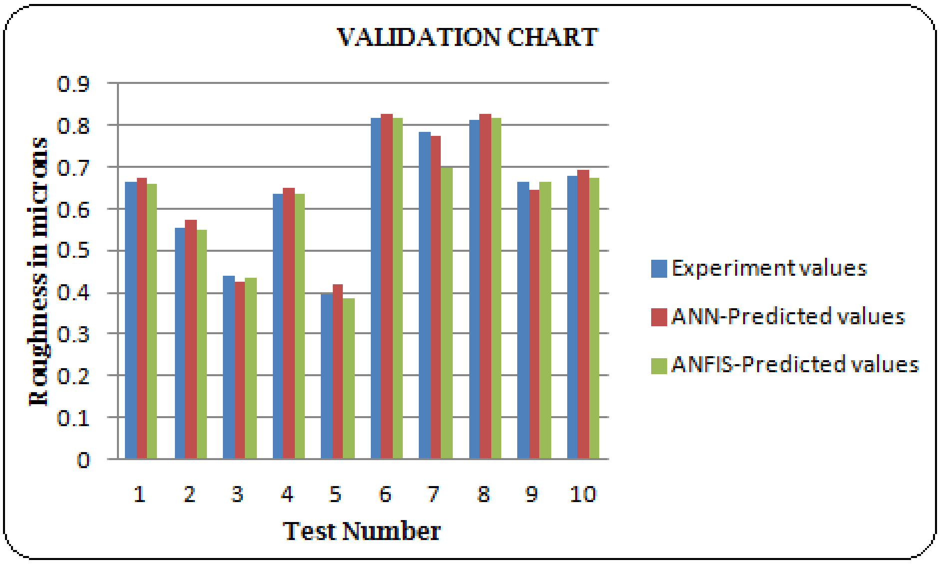

Fig. 16: Validation Performance of ANFIS with ANN.

The testing output performance of both ANN and ANFIS are shown in Fig. 14 and 15 respectively. The Validation Performance of ANFIS versus ANN is shown in Fig. 16. The % of error between the predicted values and experimental values are calculated by the given formula.

$$\%\ of\ Error = \frac{Predicted\ value - Experimental\ value}{Experimental\ value} \times 100 \quad (29)$$

In ANFIS model, the average absolute percentage error is 1.68 whereas in ANN model, the average absolute percentage error is 2.47. From the performance of ANN and ANFIS models in terms of average absolute percentage error, it is observed that the ANFIS model outperforms ANN. It may be noted that for an ANN model, the modeler has to perform a trial and error procedure to develop the optimal network architecture while such procedure is not required in developing an ANFIS model. Another feature which makes the ANFIS superior to ANN is the number of training epochs required for convergence. In this present study, the ANFIS model reached the convergence in 10 epochs while the ANN model took 27 epochs, implying considerable savings in computational time for ANFIS model. The result shows that the ANFIS model preserves the full potential of ANN model in its performance. Experimental results have shown that the proposed machine vision system can be implemented for automated prediction of surface roughness with accuracy of 98.32%. The solution accuracy greatly depends on the experimental setup and the image measurement system configuration. It is difficult to ensure absolute flatness during the image acquisition of turned components. This drawback can be eliminated by using image processing algorithm. The solution accuracy may be further enhanced by using high-resolution frame-grabber card in the machine vision system and with the use of shadow removal algorithm and appropriate image processing techniques.

7 CONCLUSION

This paper proposes an ANFIS method to establish the accurate relationship between the input parameters of Cutting speed, feed rate, depth of cut, major peak frequency, principal component magnitude squared value, average grey level and output response of surface roughness. It is observed that the proposed ANFIS based model outperforms the ANN model in terms of modeling and prediction accuracy. The results are encouraging that machine vision system can be extended too many real time industrial inspection applications.

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