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A Fuzzy-Net-Based Multilevel In-process Surface Roughness Recognition System in Milling Operations

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This paper describes a fuzzy-nets approach for a multilevel in-process surface roughness recognition (FN-M-ISRR) system, the goal of which is to predict surface roughness (R_a) under multiple cutting conditions determined by tool material, workpiece material, tool size, etc. Surface roughness was measured indirectly by extrapolation from vibration signal and cutting condition data, which were collected in real-time by an accelerometer sensor. These data were analysed and a model was constructed using a neural fuzzy system. Experimental results showed that parameters of spindle speed, feedrate, depth of cut, and vibration variables could predict surface roughness (R_a) under eight different combinations of tool and workpiece characteristics. This neural fuzzy system is shown to predict surface roughness (R_a) with 90% prediction accuracy during a milling operation.

Keywords: Accelerometer; Milling; Neural fuzzy system; Surface roughness

1. Introduction

Increasingly, research in manufacturing processes and systems is evaluating processes to improve their efficiency, productivity, and quality. The quality of finished products is defined by how closely the finished product adheres to certain specifications, including dimensions and surface quality. Surface quality is defined and identified by the combination of surface finish, surface texture, and surface roughness. Surface roughness (R_a) is the commonest index for determining surface quality.

Many lifelong functional attributes of products are determined by specific surface-quality characteristics. Paint or coating adherence, surface reflectivity, and frictional attributes are all significantly influenced by surface roughness. Poor surface quality may stop applied surfaces from adhering properly; parts may not assemble correctly owing to excessive friction resulting from a poorly-machined surface. Most industrial operations currently control surface roughness off-line when processes have ceased, leading to lowered productivity and increased material waste. Competition between industrial firms has driven the development of more efficient quality control techniques, and on-line surface roughness recognition systems are one such technique. Therefore, research concerning accurate, flexible, in-process surface roughness measurement techniques benefits manufacturing firms that seek to improve their efficiency.

1.1 Surface Roughness Measurement Techniques

Historically and contemporaneously, most surface roughness measurements have been conducted off-line after machining has ceased. For off-line measurements to be taken, the machined part(s) must be removed from the machining centre and/or the machine must be shut down completely. The required downtime scheduled for the off-line inspection process raises production costs and risks wasting materials, thus lowering efficiency. For that reason, workers in quality-control fields [1–21] are developing in-process surface roughness recognition (ISRR) systems that decrease production costs by eliminating unnecessary inspection time. In some studies, the surface profile was measured directly with a stylus [22]. However, the use of a stylus involves negative outcomes, such as the destruction of the sensor head or damage to the surface caused by stylus–workpiece contact during high-speed surface scanning. Although profile measurement has also been accomplished using a vibratory stylus [23], this contact technique has not been proved to be suitable for in-process measurements. Because of the relative disadvantages of contact methods, more research concerning in-process measurement has focused on non-contact methodologies to achieve real-time surface roughness measurement.

One non-contact R_a detection methodology is the optical method. Although various in-process, optical R_a measurement techniques have been reported [1–14], all have limited in-process uses. For example, in harsh machining environments, chip flow, machine-tool–workpiece vibration, cutting fluids, and other extraneous materials have been shown to affect

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measurement accuracy significantly. In processes using multiple materials, parametric methods must be carefully correlated for each material with different reflection characteristics.

Non-optical, non-contact instruments which have been studied as a means of in-process measurement include the inductance pickup and the capacitance probe [15,16]. The inductance pickup is placed in close proximity to the surface to measure the inductance, giving a parametric value that may be used to estimate a comparative roughness. This kind of system is limited to measuring magnetic materials, and is adversely affected by the presence of cutting fluid and chips.

Another non-contact R_a measurement technique involves the use of an ultrasonic sensor to provide a profile measurement [17–20]. A spherically focused ultrasonic sensor is positioned with a non-normal incidence angle above the surface. The sensor sends an ultrasonic pulse to the surface and measures the amplitude of the returned signal. A personal computer then analyses these data and calculates the roughness parameters. Similarly to optical measurement methods, the accuracy of this technique depends upon the detection angle and the distance between the sensor and the workpiece; it suffers from the same limitations that apply to optical methods.

1.2 Purpose of Study

Lou and Chen [21] used accelerometer sensors in their in-process surface roughness prediction system and concluded that a system combining information from vibration signals with information from cutting parameters could predict R_a on-line and in real-time. Their study attained approximately 90% prediction accuracy . However, their systems measured only one type of material, using one type of tool. Metal-cutting industries use tools and workpieces made from several different types of materials, so Lou and Chen's work could not be fully implemented industrially. The purpose of this study is to develop a more flexible approach to R_a prediction using neural-fuzzy systems as part of a multilevel in-process surface roughness recognition (M-ISRR) system that measures R_a in-process under different tool and workpiece combinations.

2. Architecture of the FN-M-ISRR System

The architecture of the fuzzy-nets based multilevel in-process surface roughness recognition (FN-M-ISRR) system for in-process tool breakage monitoring is shown schematically in Fig. 1. Three variables are input into this system:

1. The average vibration value (V_i), which is a calculation from the signals received from the accelerometer and proximity sensors.
2. The cutting parameters including spindle speed (r.p.m.), feedrate (f), and depth of cut (d).
3. The crisp parameters including tool diameter (either 0.5″ or 0.75″) and type of tool material (aluminium or steel).

Given these input states, which were obtained from the machining process, the FN-M-ISRR system predicted R_a by implementing an inference scheme based on a fuzzy-nets controller.

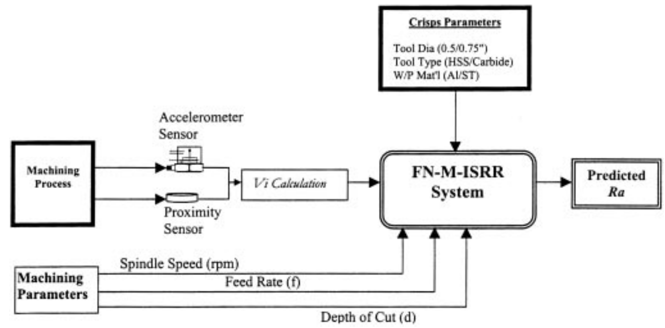


Fig. 1. Architecture of the FN-M-ISRR system.

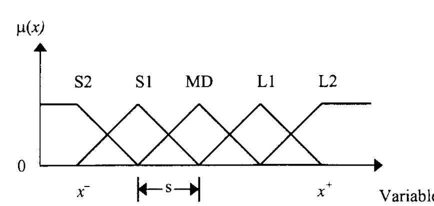
Generally, the rule bank of a fuzzy logic system is developed through expert-experience; however, the present system was designed to adapt to signals received periodically during machining. Therefore, an important step in this work was to supply a self-learning mechanism into the fuzzy logic platform. The FN-M-ISRR used fuzzy-nets (FN) systems, the architecture of which is shown in Fig. 2 [24]. The membership functions in layer 2 and the fuzzy rule base in layer 3 of the FN systems were highly dependent upon particular characteristics of individual machines. Therefore, a five-step learning procedure was proposed for generating fuzzy associative membership rules for this system.

2.1 The Five-Step Learning Mechanism

The five-step learning mechanism [24] of this FN-M-ISRR system is summarised as follows.

Step 1. Divide Input Space into Fuzzy Regions (Membership Function MF)

Input variables in this study were feedrate (F), spindle speed (S), depth of cut (D), vibration average per revolution (V), tool diameter (T), tool materials (TM), and workpiece material (WM). R_a was the output variable. Since the input variables (T, TM, and WM) were crisp parameters, no fuzzy membership functions were defined for them. Initially, the number of fuzzy



Variable	Range	Unit
Spindle speed (S)	[1400, 2000]	Rotation per minute
Feed rate (F)	[5, 19]	Inch per minute
Depth of cut (D)	[0.005, 0.039]	Inch
Vibration (V)	Based on experiments	μ Volt
$R_{a\text{ - Output}}$	Based on experiments	μ inch

Fig. 2. The domain intervals of the input–output variable and the triangular memberhsip function.

membership (FM) for each input–output sector was 3, 3, 3, 5, 7 for the input–output fuzzy spaces X_F, X_S, X_D, X_V, and Y_{R_a}, respectively. The range of each factor and their terms are shown in Fig. 2.

Although many types of algorithm have been used to define membership functions, this study used a triangular membership function (Eq. (1)) [25].

$$\text{Triangle}\,(x; a, b, c) = \begin{cases} 0 & (x \le a) \\ \dfrac{x-a}{b-a} & (a \le x \le b) \\ \dfrac{c-x}{c-b} & (b \le x \le c) \\ 0 & (c \le x) \end{cases} \qquad (1)$$

The spread of the input feature was

$$s = \frac{x_i^+ - x_i^-}{2N} \quad (i = 1, 2, \ldots, k) \qquad (2)$$

where x_i^+ and x_i^- are the domain intervals of variable x_i, $x_i \in X_i$. There were $2N$+1 fuzzy regions quantifying the universe of discourse X_i. Figure 2 depicts an example of the domain interval of the input–output variable as well as the range of each variable. The centre-points of each linguistic variable were (Eq. (3)):

$$(x_i^-, x_i^- + s, \ldots, x_i^- + (2N-1)s, x_i^+) \qquad (3)$$

Step 2. Generate Fuzzy Rules from Given Data Pairs Through Experimentation

The experimental data were collected and found to contain input–output pairs for generating fuzzy rules based on machining processes. The input–output pair data is expressed as:

$$[F^i, S^i, D^i, V^i, Ra^i] \qquad (4)$$

where i denotes the number of input–output pairs.

Once the data set was obtained, the degrees of each variable of each data pair were determined by the function:

$$\mu(x_i) = \begin{cases} 1 - \dfrac{|x_i - x_c|}{x_s} & (x_i \in [x_c, x_c + x_s]) \\ 1 - \dfrac{|x_c - x_i|}{x_s} & (x_i \in [x_c - x_s, x_c]) \\ 0 & (\text{otherwise}) \end{cases} \qquad (5)$$

where x_c is the centre of the linguistic level x and x_s is the width of the linguistic level x equal to s.

After all input and output elements were determined, each element was assigned to the region with the maximum degree. One rule from one experimental pair of the input–output data was assigned. For example, the degree of one input–output pair: $[F^1, S^1, D^1, V^1, R_a^1]$ (Fig. 3) was determined by Eq. (5) as:

$$\mu(F^1) = \{0.9 \in L1, 0.1 \in MD\}$$
$$\mu(S^1) = \{0.6 \in S1, 0.4 \in MD\}$$
$$\mu(D^1) = \{0.8 \in MD, 0.2 \in S1\}$$
$$\mu(V^1) = \{0.3 \in L1, 0.7 \in MD\}$$
$$\mu(R_a^1) = \{0.7 \in S3, 0.3 \in S2\} \qquad (6)$$

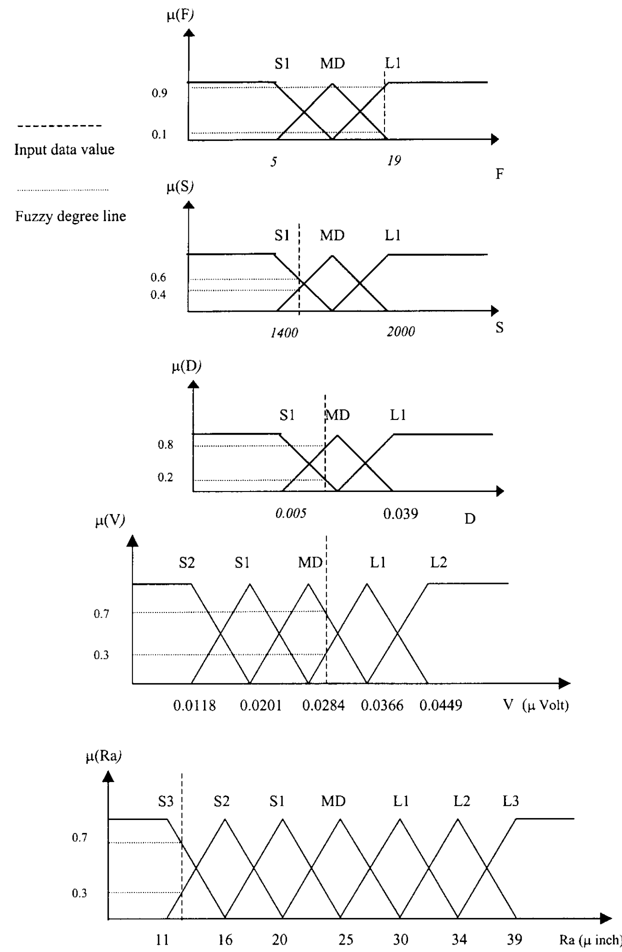


Fig. 3. An example of one input–output datum sector associated with membership functions.

The region of each variable with the maximum degree was:

$$F^1 \in L1, S^1 \in S1, D^1 \in MD, V^1 \in MD, Ra^1 \in S3 \qquad (7)$$

Thus, this experimental data set formed a fuzzy rule:

IF
(F^1 is $L1$ AND S^1 is $S1$ AND D^1 is MD AND V^1 is MD)
THEN (*Ra^1 is S3*)

Once every experimental datum was linked to a rule using the aforementioned technique, there was a high possibility that conflicting rules would cause prediction errors. Therefore, a methodology was developed to resolve conflicting rules. This will be discussed next.

Step 3. Resolve Conflicting Rules as Needed

Two or more rules conflict when they have the same IF condition but different THEN actions. Take the conflicting following rules as an example:

IF (F^1 is $L1$ AND S^1 is $S1$ AND D^1 is MD) THEN (R_a is $L2$)
IF (F^1 is $L1$ AND S^1 is $S1$ AND D^1 is MD) THEN (R_a is $L3$)

These rules can also be expressed as:

Rule i = IF (F^1 is $L1$ AND S^1 is $S1$ AND D^1 is MD) THEN (R_a^1 is $L2$) (8)

Rule j = IF (F^1 is $L1$ AND S^1 is $S1$ AND D^1 is MD) THEN (R_a^1 is $L3$) (9)

Clearly, rules i and j are in conflict. To resolve conflicts like this, the two following actions were used: either (i) the rule that occurred most frequently was chosen over the less frequent rule; or, (ii) if each rule occurred as frequently as the other, a top-down methodology was implemented to assign a degree to each rule. The degree of rule i (Eq. (8)) was defined as:

$$\text{d(rule } i) = \mu_{L1}(x_1) \times \mu_{S1}(x_2) \times \mu_{MD}(x_3) \times \mu_{L2}(y) \tag{10}$$

where $L1$, $S1$, MD, and $L2$ are linguistic values for the input vector and the output. Similarly, the degree of rule j was defined as:

$$\text{d(rule } j) = \mu_{L1}(x_1) \times \mu_{S1}(x_2) \times \mu_{MD}(x_3) \times \mu_{L3}(y) \tag{11}$$

If the magnitude of the difference $|\text{d(rule } i) - \text{d(rule } j)| > \epsilon$, (where ϵ is a user-defined parameter normally between 0 and 0.05), then the rule with the maximum degree was chosen. Otherwise, a bottom-up methodology, which added two more regions to one feature of the input vector, was used to solve this problem. For example, x_1 was initially divided into three regions. If the above difference between d(rule i) and d(rule j) was less than ϵ, then x_1 was extended into five (3+2) regions. This procedure retrained all previously trained input–output data sets and was continuously repeated in other features (x_2, …, x_k) until conflicts were eliminated.

Step 4. Create a Combined Rule Base

After resolving all conflicting rules, a fuzzy rule bank was established. Since the input vector was a 4D space, the fuzzy rule bank in this study involved a 4D matrix. An example of a 2D rule bank with a 5 × 5 fuzzy rule bank is displayed in Fig. 4. For instance, assume a rule "IF {x_1 is L_1 and x_2 is S_2}, THEN {y is L_2}" is established. In this case, L_2 fills the cell, as indicated in Fig. 4.

Step 5. Defuzzification for Prediction

After the fuzzy rule bank was established, the fuzzy-nets model could be integrated with the prediction system using a proper defuzzification process. Defuzzification methods were used to obtain a crisp value extracted from a fuzzy set as a representative value. Defuzzification includes centroid of area, maximum selector, and minimum selector methods [24]. In this study, the centroid of area method was applied:

$$y = \frac{\sum \mu_o^i y^i}{\sum \mu_o^i} \tag{12}$$

where $\mu_o^i = \min\{\mu(X_1^i), \mu(X_2^i), \ldots, \mu(X_n^i)\}$, y^i = the centre value of the regions, and y = the output for a given input vector, which was the predicted R_a value in this study.

This five-step fuzzy-nets approach integrates the neural networks and fuzzy logic systems to facilitate a simple training technique for a complex system such as a machining process. To understand the implementation in a practical set-up for the FNIP system, a physical experimental set-up and test were required to verify the approach. The experimental set-up and procedures are described in the next section.

		X_1: S2	S1	MD	L1	L2
	S2					
	S1				L2	
X_2	MD					
	L1					
	L2					

Fig. 4. Fuzzy rule bank example with rule: IF (x_1 is L_1 and x_2 is S_2), Then (y is L_2).

3. Experimental Procedures

3.1 Hardware Set-up

In any study, equipment and hardware play critical roles in conducting a viable experiment and collecting results consistent with the purpose of the study. A fundamental knowledge of the computer/machining equipment and data acquisition devices, which include proximity sensors, accelerometers, and signal converters (i.e. analogue to digital or digital to analogue), is central to understanding the activities conducted here. Accordingly, this section describes the hardware and its use.

The hardware set-up of this study is shown in Fig. 5. All machining was completed in a Fadal VMC-40 vertical machining centre with multiple tool-change capability. This machine is capable of 3-axis movement (along the x, y, and z planes). Programs can be developed in the VMC c.p.u. or downloaded from a 3½ in diskette or data link. Information was collected

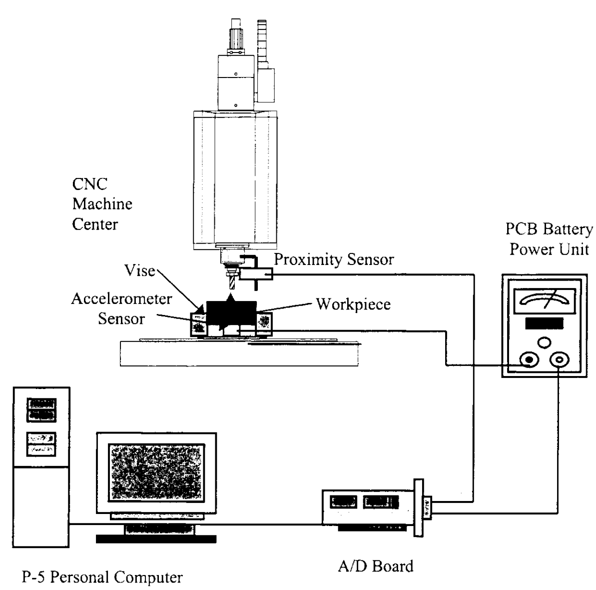


Fig. 5. Hardware set-up of the FN-M-ISRR system.

using a 353B33 accelerometer and a micro switch 922-Series 3-wire d.c. proximity sensor. The accelerometer was used to collect vibration data generated by the cutting action of the work tool, and the proximity sensor was used to count the rotations of the spindle as the tool was cutting. The proximity information was then plotted along with accelerometer data, which enabled the identification of vibrations produced during different phases of the cutting sequence. Signal data from both sensors were converted from analogue to digital by an Omega CIO-DAS-1602/12 A/D converter. The A/D converter-output was connected to a Pentium I personal computer via an I/O interface (Fig. 5).

Two power supplies were used. One power supply amplified the signal from the accelerometer, and this amplified signal was then sent to the A/D board. The second power supply powered the proximity sensor and related circuitry. A signal produced during the switched phase of the proximity sensor was sent to the A/D board on a separate channel from that used for the accelerometer signal.

The workpiece materials used in this work were 6061 aluminium and 1018 steel blocks, originally 1 in^3 in size. Various feed and spindle speeds, depths of cut, work materials, tool materials and types, and tool diameters were tested.

The Federal PocketSurf stylus profilometer was used off-line to measure the surface roughness value of machined samples. This instrument used a tracer or pickup incorporating a diamond stylus and a transducer able to generate electrical signals as it moved across the surface to be measured [21]. The surface finish measurements were made off-line with the roughness average R_a values rated in microinches (μi).

3.2 Software Set-up

Figure 6 demonstrates the integration of the software set-up of the FN-M-ISRR system. The software set-up consisted of:

1. A CNC machining program written for cutting workpieces at different spindle speeds, feedrates, and depths of cut.
2. The A/D converting program developed in the C programming language to receive accelerometer and proximity signals during an experimental run. An example of the signal received from this program is shown in Fig. 7.
3. Since the average magnitude of the tool–workpiece vibration signal (V) is an input to the FN-M-ISRR system, a vibration average (V_i) calculation program was developed in the C programming language. The following equation indicates the method of calculating the three average vibration values.

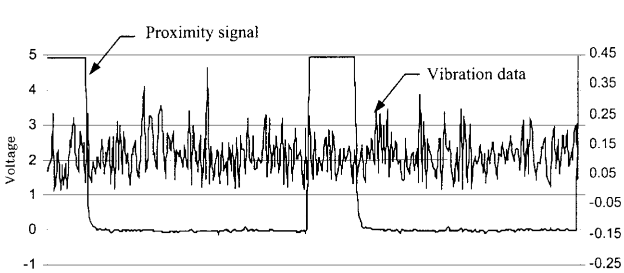


Fig. 6. Sample vibration and proximity signal.

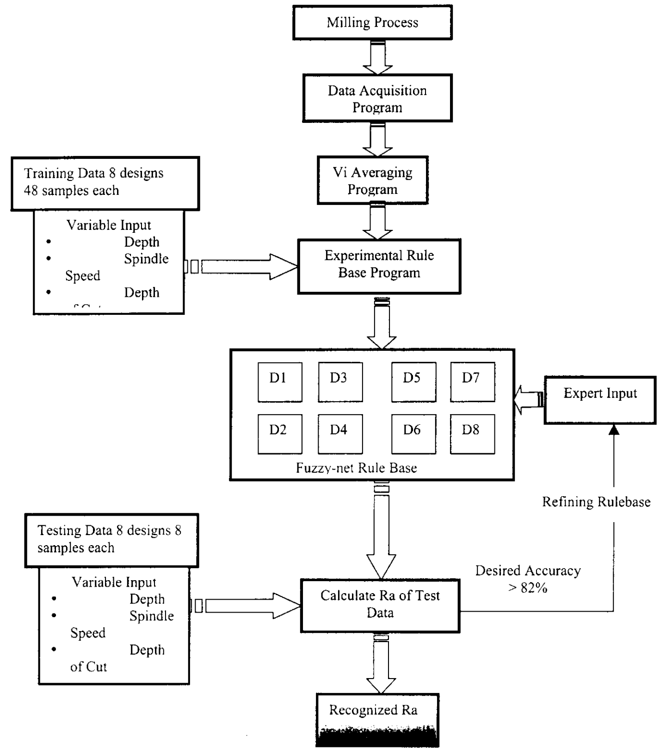


Fig. 7. Software set-up.

$$V_i = \sum_{j=(i-1)k}^{ik} |V_j|/k \quad (i = 1, 2, 3) \tag{13}$$

where k represents the total number of data items in each revolution (as indicated in Fig. 6). For example, if $i = 1$, then V_i was calculated through the vibration data points from point number 0 to point number k (for a total of k data points in one revolution). Therefore, three V_i values were gathered within one experimental run, and all these data pairs were used for the fuzzy-nets learning procedures. Note that the vibration average (V_i) was measured in volts.

4. After the data sets were gathered experimentally, a C program based on the FN-M-ISRR system was designed to generate a fuzzy rule base and eventually to recognise processing of the R_a value while the input data set was received through experimentation. The rule base for each design (a total of 8 designs were discussed) was developed by the rule base program and from expert input. The R_a recognition program integrated the combined rule base and testing data to predict the R_a value given the cutting parameter and vibration signals.

3.3 Design for Training and Testing Data Sets

In order to provide proper learning, a series of experimental runs was required to conduct this multilevel in-process surface roughness recognition system in end milling operations. Table 1 shows the parameters and settings of samples collected as training data for the fuzzy-nets model rule base. A total of 384 experimental runs were carried out for each of the 8

Table 1. Parameters and settings for the training data for each of 8 designs.

Feed (i.p.m.)	Depth (in)	r.p.m.
8	0.01	1500
11	0.02	1667
14	0.03	1833
16		2000

designs in this study. Within these experimental runs, some data were also used for testing. In addition to these experimental runs, a total of 64 runs (as shown in Table 2) was performed to gather testing data for evaluating the accuracy of the proposed model.

3.4 Evaluation Approach

Consider one particular design, j, which included a tool diameter of 0.5″, HSS tool material, and steel workpiece material. The surface of each test workpiece was measured using a profilometer in order to obtain an measured R_{aij}. The surface roughness prediction obtained through this proposed FN-M-ISRR system was R'_{aij}. Therefore, the deviation of each testing sample under design j was denoted by ϕ_{kj} and was defined as:

$$\phi_{kj} = \frac{|R_{a_{ij}} - R'_{a_{ij}}|}{R_{a_{ij}}} \times 100\% \tag{14}$$

After the deviation of each testing sample under design j was determined, the average of deviation of each design (j) was calculated (Eq. (15)):

$$\bar{\phi}_j = \frac{\sum_{k=1}^{m} \phi_{kj}}{m}, \tag{15}$$

where m = number of samples within each design (in this case, $m = 8$).

After the deviation of each design was calculated, the overall average for the FN-M-ISRR system was defined as:

$$\bar{\bar{\phi}} = \frac{\sum_{j=1}^{n} \bar{\phi}_j}{n} \tag{16}$$

where n is the number of designs (in this case, $n = 8$).

Table 2. Parameters and settings for the testing data (8 cutting conditions × 8 designs = 64 testing data sets)

Feed (i.p.m.)	Depth (in)	r.p.m.
10	0.015	1583
14	0.025	1917

3.5 Experimental Results and Summary

After 384 experimental runs, eight fuzzy rule bases were successfully developed for eight designs. A total of 135 rules were created for each design. The fuzzy-net rule base was developed according to the fuzzy-net methodology explained in Section 2. The recognition accuracy of this proposed FN-M-ISRR system is summarised in Table 3.

4. Conclusion and Remarks

1. The fuzzy-net-based model of the multilevel ISRR system was developed from the fuzzy-nets theory to extract fuzzy rules from the training data. In this research, the fuzzy-nets model demonstrated the use of learning and reasoning capabilities to establish a fuzzy rule bank for various tool diameter, tool material, and workpiece material combinations. The overall FN-M-ISRR system demonstrated a 90% accuracy of prediction average, and is a promising step for further development in in-process surface roughness recognition systems. However, some directions for further research could enhance this system for future implementation. For example, feedback control is necessary for further study in automated production systems. The FN-M-ISRR system should be a closed-loop system, so that the output of the system could feed back to the CNC machine centre, allowing feedrate to adjust to surface roughness quality specifications from the designer. Thus, there is a need for further study addressing interface techniques between the FN-M-ISRR system and the CNC machining centre.
2. The proposed FN-M-ISRR system was based on a software platform and controlled by a personal computer system. To increase operation speed, minimise size, reduce costs, and enhance efficiency, the FN-M-ISRR system could be developed in a hardware setting operated by microprocessor, fuzzy chip, memory chip, and other related circuits. These kinds of technique are important and may be necessary for further development of non-contact approaches to measuring surface roughness on-line.

Table 3. The overall accuracy for the FN-M-ISRR system using the testing data sets

Design (j)	Design configuration	Average deviation for fuzzy net model	Samples (m)
1	$TD_1TM_1WM_1$	0.0773	8
2	$TD_1TM_1WM_2$	0.0956	8
3	$TD_1TM_2WM_1$	0.1525	8
4	$TD_1TM_2WM_2$	0.1650	8
5	$TD_2TM_1WM_1$	0.0859	8
6	$TD_2TM_1WM_2$	0.0739	8
7	$TD_2TM_2WM_1$	0.0635	8
8	$TD_2TM_2WM_2$	0.1247	8
Total $n = 8$		10.5%	64
Accuracy		90%	

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This paper is equally contributed by the authors; the author list is in alphabetical order.

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