Int J Adv Manuf Technol (1999) 15:231–237

The International Journal of
Advanced Manufacturing Technology

Fuzzy Nets Based on-line Cutting Power Recognition in Milling Operations

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A self-organising fuzzy-nets optimisation system was developed to generate a knowledge bank able to demonstrate the required cutting power on-line for a short length of time in an NC verifier. This fuzzy-nets system (FNS) uses a five-step self-learning procedure, and was examined for end-milling operations on a Fadal VMC40 vertical machining centre. Data collected from the operations were used to train and test the FNS. Three approaches were employed to predict the cutting power:

1. *Metal cutting theory model.*
2. *Fuzzy-nets model using theoretical data for training.*
3. *Fuzzy-nets model using experimental data for training.*

To compare the quality of the data obtained from these approaches, three hypotheses were formulated for this study. The results showed that the FNS possessed a satisfactory range of accuracy with the intended applications of the model.

Keywords: CAD/CAM; CNC programming; Cutting force; Dynamometer; Fuzzy-nets system; Machining parameters; Machining processes; Specific energy

1. Introduction

The optimisation of machining processes has been studied by many researchers using different approaches. One major focus is to monitor the tool condition throughout the machining process. Control systems for chatter vibration, tool wear, and tool breakage have been applied in developing an on-line real-time approach [1–7]. Another focus of machining control research attempts to determine the cutting power for any specific machine in a CAD/CAM platform or in an on-line real-time machining control system. In this research, the latter focus is discussed, and some of the current research reports are summarised.

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Bouzakis et al. presented a computer-supported procedure for optimising the cutting speed and feedrate in 3-axis milling [8]. The input to that procedure is obtained from the NC code of a part. Next, the tool motions, derived from the NC code, are grouped into subprocesses and the optimal feedrate and cutting-speed values along the tool path are calculated using the developed models. These optimal cutting conditions are automatically implemented into the NC code.

The unified mechanics of the cutting approach and modular software structure applied to developing models for quantitative prediction of force components, torque, and power for practical machining operations were reviewed by Armarego and Deshpande [9]. This approach has been used to develop three predictive models and computer programs common to peripheral milling, end milling, and slotting.

Mesquita et al. also presented a model and an interactive program system (MECCANO2) for the multiple-criteria selection of optimal machining conditions in multipass turning [10]. Optimisation is carried out for the most important machining conditions: cutting speed (*Sc*); feedrate (*Fr*); and depth of cut (*Dc*). This optimisation followed criteria consisting of minimum unit production cost, minimum unit production time, and minimum number of passes. The user can specify the values of the model parameters, criterion weights, and desired tool life. Furthermore, MECCANO2 provides a graphical representation of the results, making it very suitable for application in an educational environment.

A computer-aided cutting simulation system has been developed to model 3D NC end-milling operations in which the varying axial and radial depths of cut in an NC tool path are identified by a modelling system using constructive solid geometry and boundary representation techniques [11]. Once the axial and radial depths of cut are determined, the dynamic cutting force is calculated from an end-milling process model. As a result, the cutting performance in 3D NC end-milling operations can be verified and optimised.

Fang and Jawahi presented a new methodology for predicting total machining performance (TMP), including such factors as surface finish, tool wear rate, dimensional accuracy, cutting power, and chip breakability [12]. In this new methodology, a series of fuzzy-set models were developed to give quantitative assessments of the TMP for any given set of input conditions, including work material properties, tool geometry, chip breaker types, and cutting conditions.

Based on these literature reviews, this study focuses on developing an adaptive cutting-power prediction model for CAD/CAM systems. Three approaches for obtaining cutting power are evaluated:

1. Theory model – using the machining mechanics algorithm.
2. Theory and fuzzy-nets model – using the cutting forces gathered from the machining mechanics algorithm to train the fuzzy-nets system.
3. Experiment and fuzzy-nets model – using the cutting forces generated from experiments to train the fuzzy-nets system.

In order to compare these approaches, three hypotheses are evaluated. The organisation of this paper is described below.

The machining mechanics and the fuzzy-nets training system are presented in Section 2. The fuzzy-nets model and experimentation are demonstrated in Section 3, and Section 4 presents the hypotheses and results. Finally, conclusions and comments for this research are presented in Section 5.

2. Three Cutting Force Prediction Models

Three approaches for predicting instant cutting force during the end-milling operation are:

1. Theory model – using the machining mechanics algorithm.
2. Theory and fuzzy-nets – using the cutting forces gathered from the machining mechanics algorithm to train the fuzzy-nets system.
3. Experiment and fuzzy-nets – using the cutting forces generated from experiments to train the fuzzy-nets system.

In this section, the models of machining mechanics and fuzzy-nets training procedure are presented.

2.1 Theory Model in Predicting Cutting Force

The cutting power (P_c) is calculated by the formula

$$P_c = MRR\ U\ FCF\ WCF \tag{1}$$

where *MRR* is the material removal rate, $\text{mm}^3\,\text{s}^{-1}$; *U* is the unit power or specific energy, N-m mm^{-3}; *FCF* is feed correction factor; and *WCF* is the tool wear correction factor. For the aluminium used in this study, the value of *WCF* is 1.1 and the value of *U* is 0.8274 N-m mm^{-3} [13]. Table 1 shows some feeds and their corresponding correction factors. The correction factors for other feeds can be determined by interpolation.

The material removal rate is calculated by the formula

Table 1. Feed correction factors for unit horsepower and specific energy.

Feed (m.m.p.t.)	0.025	0.075	0.125	0.175	0.225	0.275	0.325
FCF	1.6	1.4	1.25	1.18	1.06	0.95	0.92

$$MRR = W\ H\ Fr \tag{2}$$

where *W* is the width of cut (mm), *H* is the depth of cut (mm), and *Fr* is the feedrate, mm s^{-1}.

The feed rate (*Fr*) is calculated by the formula

$$Fr = Ft\ T\ N \tag{3}$$

where *Ft* is the feed, *T* is the number of teeth, a constant, and *N* represents speed in r.p.s.

The speed *N* is calculated by the formula

$$N = \frac{S\ 1000}{\pi\ D\ 60} \tag{4}$$

where *S* represents surface speed in mpm, π is the constant 3.1416, and *D* is tool diameter in imm.

By combining Eqs (1), (2), (3) and (4), the cutting power (P_c) can be calculated by the following equation (assume $T = 4$)

$$P_c = H\ Ft\ S\ 17.558\ FCF\ 1.1 \tag{5}$$

After obtaining the cutting force by providing cutting parameters, the cutting force data was trained using the fuzzy-nets model to obtain the quick response cutting force for linkage with the CAD/CAM system.

2.2 Fuzzy-Nets Model

Before this model is discussed, the summary of fuzzy-nets training is presented. The fuzzy-nets training approach, introduced by Chen [14] consists of five steps:

Step 1: Define the fuzzy regions of the input and output spaces

The purpose of the fuzzy-nets model is to verify milling operations. The inputs to the model are speed, feedrate, and depth of cut. The input feature vector is defined as [*Sc*, *Fr*, *Dc*].

The spread of an input feature *I* is calculated by the equation

$$s = \frac{X_{\max} - X_{\min}}{N - 1} \tag{6}$$

where $X_{\max}$ is the maximum value of the input feature *I*, $X_{\min}$ is the minimum value of the input feature *I*, and *N* represents the number of regions of the input feature *I*.

The centre of each linguistic variable is determined by

$$(X_{\min}, X_{\min} + s, \ldots, X_{\min} + s(N-2), X_{\max}) \tag{7}$$

For example, the surface speed (*Sc*) is considered to be from 18 m.p.m. to 58 m.p.m. The shape of each membership function is triangular and the width of spread of each triangular function is identical. Assuming that the three regions of each variable are defined, the spread of the surface speed is shown to be 20 m.p.m. Consequently, the centre-points of each linguistic variable (*S*, *M*, *L*) for surface speed are 18, 38, 58, as shown in Fig. 1.

Step 2: Generate the fuzzy rules from given data-pairs through experimentation

There are two ways to obtain the training data; one is from machining handbooks, the other is from experiments. The data will consist of the following elements:

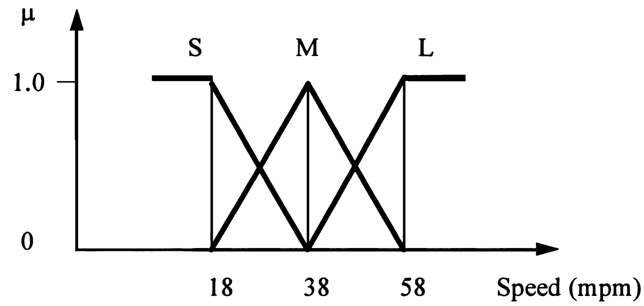

Fig. 1. Centre-points of linguistic variables small, medium, and large.

$$[Sc^{(i)}, Fr^{(i)}, Dc^{(i)}, Pc^{(i)}, \mu^{(i)}_{d^{(i)}}] \tag{8}$$

where i denotes the number of the training data set, and μ_d denotes a degree of this data set assigned by a human expert. The degree (μ_d) represents the usefulness of the data-pair.

The degrees of each input and output feature are determined in different regions. The function used to calculate the degrees is given as:

$$\mu_{x_c,x_s}(x_i) = \begin{cases} 1 - \dfrac{X_c - x_i}{X_s\, x_i}, & x_i \in [X_c - X_s, X_c] \\ \dfrac{x_i - X_c}{X_s x_i}, & x_i \in [X_c, X_c + X_s] \\ 0, & otherwise \end{cases} \tag{9}$$

where X_c and X_s indicate the centre-point and the spread width, respectively, of the linguistic level X.

For example, if the input vector of an experimental cut has been set at [49 m.p.m., 0.14 m.m.p.t., 1.7 mm] and the Pc value obtained from the A/D board was 240 W (watts), as shown in Fig. 2, the degrees of input and output values are as follows:

> if $x(Sc)$ = 49 m.p.m. and $X_S(Sc)$ = 10 m.p.m.; then $\mu_{46,10}(49) = 0.7$ and $\mu_{56,10}$ (49) = 0.3 (i.e. the Sc input value of 49 m.p.m. has a degree 0.7 in the centre-point M and degree 0.3 in L).

Similarly, the Fr input value 0.14 m.m.p.t. has a degree of 0.2 in S and a degree of 0.8 in M, the Dc input value of 1.7 mm has a degree 0.37 in M and a degree 0.63 in L, and the Pc output value 240 W has a degree of 0.67 in S and a degree of 0.33 in M. After all the values have been assigned degrees in all regions, each value is assigned to the region with the maximum degree. Thus, Sc (49 m.p.m.) is assigned to M (degree = 0.7), Fr (0.14 m.m.p.t.) is assigned to M (degree = 0.8), Dc (1.7 mm) is assigned to L (degree = 0.63), and Pc is assigned to S (degree = 0.67).

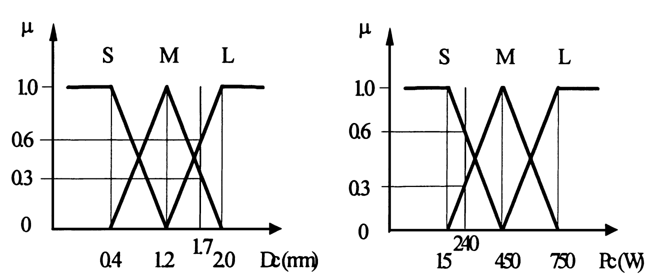

Fig. 2. Degrees of input and output values.

The input–output data-pairs define the fuzzy classification rules for the knowledge-base of the fuzzy logic system as:

> IF (Sc is A_1 AND Fr is B_1 AND Dc is C_1) THEN (the output is Pc_1) (10)

For example, if

> [Sc, Fr, Dc, Pc] $\Rightarrow$ [49 m.p.m., 0.14 m.m.p.t., 1.7 mm, 240 W] (11)

then

$$[Sc(0.7, \in M), Fr(0.8 \in M), Dc(0.63 \in L),$$
$$Pc(0.67 \in S)] \Rightarrow \text{IF } (Sc \text{ is } M \wedge Fr \text{ is } M \wedge Dc \text{ is } L)$$
$$\text{THEN } (Pc \text{ is } S) \tag{12}$$

where the symbol $\wedge$ represents the “AND” operation in classical logic. A fuzzy rule will be generated for each input–output data-pair.

Step 3: Resolve conflicting rules

It is highly possible that there will be conflicting rules, i.e. rules that have the same IF premise but a different THEN conclusion. Top-down and bottom-up methodologies are proposed to resolve this conflict. Initial use of the top-down methodology is faster, but if the conflict continues, the latter is employed for the resolving process. Top-down methodology works by assigning a degree (d) to each rule. The degree of the rule “IF Sc is M and Fr is M and Dc is L, THEN Pc is S,” is defined as:

$$d(Rule) = \mu_M(Sc)\mu_M(Fr)\mu_L(Dc)\mu_S(Pc)\mu_D \tag{13}$$

where μ_D is the data-pair degree assigned by the human expert. An example of two conflicting rules (j and k) is:

Rule j: “IF Sc is M and Fr is M and Dc is L, THEN Pc is S.” (14)

Rule K: “IF Sc is M and Fr is M and Dc is L, THEN Pc is M.” (15)

In resolving this conflict, if the magnitude of the deviation $|d(\text{rule } k) - d(\text{rule } j)| > \delta$, where $0 < \delta > 0.1$ and δ is a user-defined parameter, then the rule with the maximum active value is chosen. Otherwise, (i.e. $\delta \geq |d(\text{rule } k) - d(\text{rule } j)|$) training is suspended. A bottom-up procedure is required to resolve this problem.

Using the bottom-up methodology will add two more regions to one feature of the input vector. For example, Sc is set up initially for five regions. If the differential degree of rule j and rule k is less than δ, then Sc is extended to seven regions. Thus, all the previously trained input–output data-pairs must be retrained. If any other rules conflict, two more regions must be added to the output feature. If the conflicts are still not resolved, the number of regions of the next input feature and the output feature ((Fr, Pc), (Fr, Pc), (Dc, Pc)) is extended sequentially until all the conflicting situations are resolved.

Step 4: Develop a combined fuzzy rule base

The FNS is a 3D space classifier. A three-region fuzzy associative memory (FAM) bank is shown in Fig. 3. The following

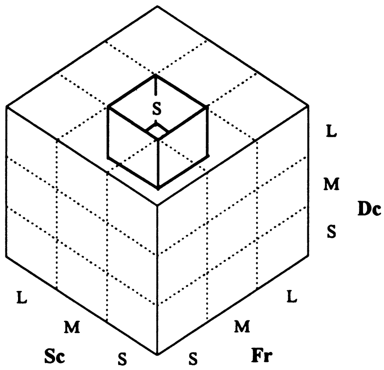

Fig. 3. A three-region FAM bank.

strategy summarises how the cells of the fuzzy rule base are filled. A combined fuzzy rule base assigns rules from the experimental data-pairs. If more than one rule in a cell indicates a conflict, top-down and bottom-up strategies are applied to resolve the problem. Since the linguistic rule is an "AND" rule in this case, only one rule will fill a cell. As described in Step 3, if rule *j* is chosen rather than rule *k*, then the region value *S* will fill the cell illustrated in Fig. 3.

Step 5: Perform defuzzification

The following defuzzification strategy is used to determine the output control *Pc* for the input vector. First, for given inputs (*Sc*, *Fr*, *Dc*), the antecedents of the fuzzy rule use the multiplication operation to determine the degree, μ_{output}, of the output control responding to the input, i.e.

$$\mu^i_{Output^i} = u^i_{Input^i_{Sc}}\ \mu^i_{Input^i_{Fr}}\ \mu^i_{Input^i_{Dc}} \tag{16}$$

where $Output^i$ denotes the output regions of rule *i*, and $Input^i$ denotes the input region of rule *i* of the input vector. The centroid defuzzification method is applied to determine the output, which is calculated based on the equation

$$y = \left(\sum_{j}^{m} \mu_{Output}(Pc_j)c(Pc_j)\right) \Bigg/ \left(\sum_{j}^{m} \mu_{Output}(Pc_j)\right) \tag{17}$$

where $c(Pc_j)$ denotes the centre of the output region, $Output^j$, and *m* is the number of adjacent fuzzy rules in the combined fuzzy rule-base.

2.3 Fuzzy-Nets Model and Machining Mechanics Algorithm

A fuzzy-nets system was developed to simulate and predict the cutting power of end-milling operations using the cutting forces gathered from the machining mechanics algorithm. The required cutting power of a CNC machine is determined by variables such as speed, feedrate, depth of cut, strength of tool material, strength of workpiece material. The relationship between cutting power and these variables is nonlinear. The purpose of this approach is to investigate and understand the milling process, verify and validate the system, and reduce experimental costs.

Three hundred and forty-three input–output data sets are created to train the fuzzy-nets system. Three hundred and forty-three rules are generated through the training procedure for the 343 cells in the rule base. After training, 20 input testing data sets are used to evaluate the performance of the system. The results show that the FNS possesses a satisfactory range of accuracy with the intended applications of the model. In order to draw a conclusion, the third model, experiment and fuzzy-nets approach, is presented in the next section.

3. Fuzzy-Nets Model and Experimentation

We believe that the cutting force varies during the cutting processes from one machining operation to the next, particularly due to the power-limitations in each individual machine. For example, a two-horsepower machine has a different rigidity capability from a five-horsepower machine. This causes the dynamics system to vary from one machine to the next. To provide a better model to incorporate into a CAD/CAM system, the research shows that using the experimental data could provide a better solution. However, it is very difficult to gather all cutting force information with all possible cutting parameters (of which there are an infinite number of combinations). Therefore, the fuzzy-nets approach is evaluated in this research for its ability to gather sample data to predict the cutting force with reasonable accuracy.

In this model, the fuzzy-nets training is basically identical to the method indicated in the previous model, the only difference being that the training data is obtained from an experimental setting. The experimental set-up is described in the next section.

3.1 Experimental Set-up

The performance of the fuzzy-nets system was examined for end-milling operations. As shown in Fig. 4, the experimental set-up comprises commercially available and custom-made hardware and software components.

A series of end-milling operations was undertaken on a Fadal VMC40 vertical machining centre using a CNC part-program written to collect data specifically for this study.

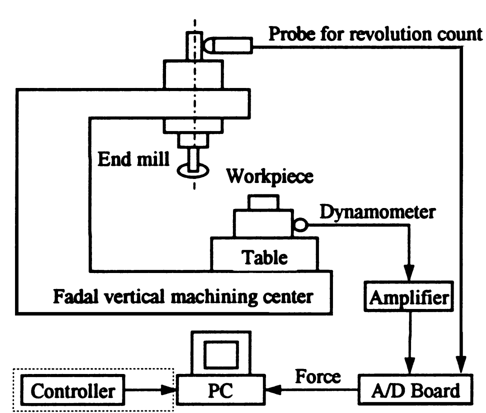

Fig. 4. Experimental set-up.

The cutting force signal was measured by a three-component dynamometer mounted on the table of the CNC machine with the workpiece. The output voltage signal of the charge amplifier was collected by a personal computer in which an Omega DAS-1401 high-performance analog-to-digital (A/D) board was installed to sample the data on-line. Data sets were collected to train and test the fuzzy-nets system.

3.2 Instrument Calibration and Set-up Evaluation

To ensure reliable operation of an instrument, it must be well-maintained and recalibrated after a specified period of time or an uncontrolled overload. The three-component dynamometer and amplifier were brand-new and consequently did not require factory-recalibration. However, the amplifier and the base and top surfaces of the dynamometer were inspected for visible damage before use. A weight scale, a probe, and test cuts were used to validate the experimental set-up.

3.3 Production Cuts and Data Collection

The workpieces were deburred and their surfaces smoothed before they were secured in the holder. This process was carried out to ensure accurate cutting results. The cutters used for this experiment were high-speed steel (HSS) end mills, 19.05 mm (0.75 inches) in diameter, with four flutes, and a 30° helix angle. Vibration during cutting could cause the experimental components to move or loosen, especially the workpiece and end mill. Another problem was presented by the *z*-axis force created by the helical shape of the end mill. This vibration could become severe when the feedrate is high and the cut deep. Therefore, the machines were inspected periodically for movement and damage.

The three orthogonal components of the force (Fx, Fy, and Fz) acting on the workpiece were measured by the Kistler three-component dynamometer, which was connected to a Kistler amplifier. The amplifier converted the piezoelectric transducer signals from the dynamometer into proportional output voltages. The voltage signals were sent to the Omega DAS-1401 A/D board, which was installed in a personal computer. Figure 5 shows an example of the signal data.

The digital data from the A/D board were then acquired and stored by the LabTech software into three files for the three force components. An additional file was created for the revolution count data from the probe. The data were also displayed on the computer monitor for inspection. The execution of the LabTech program would overwrite the files created by the previous execution. Hence, these files were copied to different locations before subsequent executions of the LabTech program. The sampling rate and duration of data acquisition were 1000 samples per second and 1.6 seconds, respectively. These settings were limited by the available random access memory (RAM) of the computer.

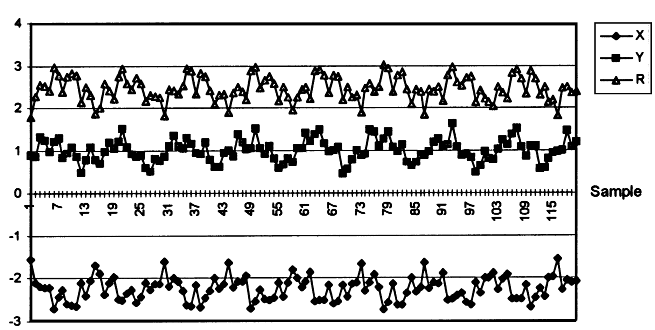

Fig. 5. Force diagram of production cuts.

A timing problem could occur during the production cuts. A cut took about 1.6 s, varying as a function of feedrate, and it took several seconds to open the LabTech program. These two events must be synchronised to avoid losing data. This problem was solved by delaying the start of either event or suspending the feed for a specified period of time by the CNC part program. The time required to move the tool from its start position to the initial cut position was calculated using the feedrates in the CNC code.

After milling is completed, material must be taken from the workpiece for the operation to continue running. The material-removal rate (MRR) describes the speed with which this is accomplished. A higher MRR uses less processing time, but requires greater power. Different formulae are used for different processes. For end milling, the MRR is calculated by the formula

$$MRR = W\ Dc\ Ft\ T\ N \tag{18}$$

where W represents the width of cut (mm), Dc is the depth of cut (mm), with Ft is the feed (mm t^{-1}), T is the number of teeth, and N is the spindle speed (r.p.m.). Assuming that W, T, and N are constants, the MRR is determined by the product of Dc and Ft. For this experiment, the product of Dc and Ft is limited to 0.765 mm^2.

Two hundred and twenty-three combinations of machining parameters (depth of cut, feedrate, and spindle speed) were selected to make production cuts. The machining settings were manually changed in the CNC part program for each run. Sometimes, each set of the machining settings required more than one run. Cutting fluids were not used in this experiment.

4. Hypothesis and Results

The required cutting power of a CNC machine is determined by variables such as speed, feedrate, depth of cut, strength of tool material, strength of workpiece material, etc. The relationship of the cutting power and these variables is nonlinear. Three approaches were developed to predict the cutting power and then evaluated to determine the quality of data in each approach. To compare data obtained from these approaches, three hypotheses were formulated as follows:

Null Hypothesis 1. There is no significant difference in cutting power between the data calculated by the fuzzy-nets system and the data collected from experimentation.

$$H_0\colon\ \mu_d = 0$$

The mean ($\bar{d}$) and standard deviation (s.d.) of the 23 difference measurements are $\bar{d}$ = 5.016 and s.d. = 22.954, respectively. Thus,

$$t = \frac{\bar{d} - 0}{s.d./\sqrt{n}} = \frac{5.016}{22.954/\sqrt{23}} = 1.048$$

The critical value of t for two-tailed statistical test is 2.508 ($\alpha = 0.02$; degrees of freedom (df) = 22). Since the observed value of t does not exceed 2.508, we conclude that there is insufficient evidence to indicate that the cutting power collected from experimentation is different from the cutting power calculated by the fuzzy-nets system, at the 0.02 level of significance. In other words, the FNS provides a satisfactory range of accuracy within the intended applications of the model.

Null Hypothesis 2. There is no significant difference in cutting power between the data collected from the experimentation and the data calculated by the formula.

$$H_0: \mu_d = 0$$

The mean ($\bar{d}$) and standard deviation (s.d.) of the 23 difference measurements are $\bar{d}$= 27.281 and s.d. = 19.606, respectively. Thus,

$$t = \frac{\bar{d} - 0}{s.d./\sqrt{n}} = \frac{27.281}{19.606/\sqrt{23}} = 6.673$$

The critical value of t for the two-tailed statistical test is 6.673, ($\alpha = 0.02$; $df = 22$). Since the observed value of t exceeds 2.508, we conclude that there is sufficient evidence to indicate that the cutting power collected from experimentation is different from the cutting power calculated by the formula. Therefore, the quality of the data collected from experimentation is better than the quality of the formula data.

Null Hypothesis 3. There is no significant difference in cutting power between the data calculated by the formula and the data calculated by the fuzzy-nets system.

$$H_0: \mu_d = 0$$

The mean ($\bar{d}$) and standard deviation (s.d.) of the 23 difference measurements are $\bar{d}$ = 22.265 and s.d. = 32.43, respectively. Thus

$$t = \frac{\bar{d} - 0}{s.d./\sqrt{n}} = \frac{22.265}{32.43/\sqrt{23}} = 3.293$$

The critical value of t for the two-tailed statistical test is 3.293, ($\alpha = 0.02$; $df = 22$). Since the observed value of t exceeds 2.508, we conclude that there is sufficient evidence to indicate that the cutting power calculated by the fuzzy-nets system is different from that calculated by the formula. Therefore, the fuzzy-nets system predicted the cutting power more accurately than the formula model.

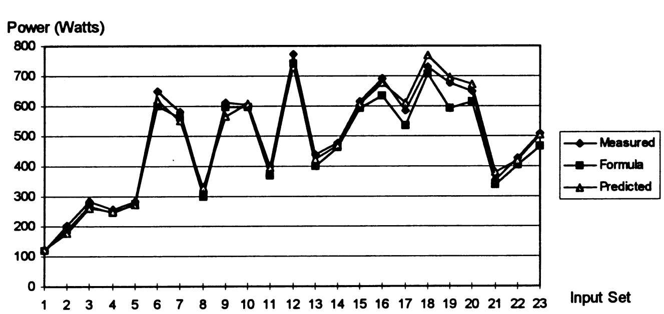

Fig. 6. Comparisons between measured, formula, and predicted cutting powers.

4.1 Summary of the Results

Table 2 and Fig. 6 summarise the results. The accuracy of data is expressed in terms of error, i.e.

$$Error\ (\%) = \frac{|Power_{Predicted} - Power_{Measured}|}{Power_{Measured}} 100\%$$

where $Power_{Predicted}$ is obtained from the formula and FNS and $Power_{Measured}$ is obtained from experimentation. The means of errors in the power calculation are 5.43% for the formula and 4.1% for the FNS. From the statistical test and the accuracy comparison, we conclude that the power calculated by the FNS is more accurate than the power calculated by the formula.

5. Conclusions and Further Research

As described in the review of literature, various researchers have attempted to produce a method for predicting cutting power and/or optimising machining performance, and they have demonstrated great success. In 1994, Fang and Jawahir developed a new methodology for predicting the total machining performance (TMP) in finish turning using integrated fuzzy-set models of machinability parameters, including cutting power [12]. In the development of the new methodology, a machining reference database is first established from experiments. Secondly, a knowledge pool is developed, based on a series of machining experiments and the existing knowledge of the major influencing factors on the TMP. Then, a fuzzy-set method is introduced to quantify the effects of these factors. Finally, several fuzzy set models are developed to quantitatively assess the TMP for any given set of input conditions. The comparisons between their study (TMP) and this study (FNS) are as follows:

1. The space to store the data and knowledge-base is less for the FNS. A machining reference database and a knowledge pool are required in the TMP study. However, all the FNS needs is the fuzzy rule base.
2. The performance of the FNS was evaluated using simulation and experimental data in various tests with combinations of input conditions, including depth of cut, feedrate, and cutting speed. The accuracy of prediction is expressed in terms of error. In this research, the mean of errors in power is 4.1% for the experimental tests, whereas in the TMP model the mean of errors is 13.5%. The FNS model is thus significantly more accurate than the TMP model.

With the above comparisons, the major conclusions drawn from this study are as follows:

1. The fuzzy-nets system was assessed for its performance.
2. Data handbooks and formulae are only for general reference. The power requirements obtained from the experiment are more accurate than the formula.

Table 2. Testing results of the fuzzy-nets system.

	Input sets			Outputs (W)					
Number	*Dc* (mm)	*Sc* (m.p.m.)	*Fr* (m.m.p.t.)	Measured	Formula	Predicted	MP-PP	MP-FP	PP-FP
1	0.4	63	0.24	118.712	119.963	122	–3.288	–1.251	2.037
2	0.68	51	0.3	202.056	187.879	177	25.056	14.177	–10.879
3	1.08	58	0.2	286.455	270.998	263	23.455	15.457	–7.998
4	1.48	65	0.1	258.786	246.182	251	7.786	12.604	4.818
5	1.7	49	0.14	285.228	276.816	274	11.228	8.412	–2.816
6	2.12	62	0.22	650.163	598.702	618	32.163	51.461	19.298
7	2.52	55	0.18	580.405	562.787	550	30.405	17.618	–12.787
8	2.92	48	0.08	315.746	299.937	331	–15.254	15.809	31.063
9	3.56	57	0.12	610.778	594.925	567	43.778	15.853	–27.925
10	3.96	64	0.09	605.254	596.929	606	–0.746	8.325	9.071
11	4.36	50	0.06	400.478	368.83	398	2.478	31.648	29.17
12	5	63	0.09	772.97	741.922	730	42.97	31.048	–11.922
13	5.4	51	0.05	440.16	398.925	422	18.16	41.235	23.075
14	5.8	47	0.06	475.988	461.207	469	6.988	14.781	7.793
15	6.44	48	0.07	614.127	593.443	607	7.127	20.684	13.557
16	6.84	55	0.06	692.283	636.486	678	14.283	55.797	41.514
17	7.24	62	0.04	582.899	534.044	613	–30.101	48.855	78.956
18	7.88	53	0.06	730.929	706.597	769	–38.071	24.332	62.403
19	8.28	60	0.04	676.503	591.055	698	–21.497	85.448	106.945
20	8.68	49	0.05	649.758	616.088	673	–23.242	33.67	56.912
21	1.8	39	0.245	352.939	337.491	381	–28.061	15.448	43.509
22	1.8	46.5	0.245	427.803	402.394	421	6.803	25.409	18.606
23	1.8	54	0.245	507.948	467.296	505	2.948	40.652	37.704

3. The new fuzzy-nets based methodology can show the process planners and CNC part programmers the required cutting power in a shorter period of time on-line.
4. The FNS can be incorporated into a CAD/CAM package to recommend optimal machining parameters.

Additional research into this field of study is required, especially in the following areas:

1. The model could be enhanced to use tools of different materials (e.g. carbide, ceramic) and/or attributes could be studied to understand their impact on the power-requirements.
2. Different materials have different physical and chemical properties. The workpiece materials used for this research were made from aluminium. Other commonly used materials, such as carbon steel and cast iron, could be investigated.
3. Other manufacturing processes, such as turning and grinding, etc., could be considered to examine the performance of the FNS.

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