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A Comparison of Speed-Feed Fuzzy Intelligent System and ANN for Machinability Data Selection of CNC Machines

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1. Introduction

The machining process exhibits piecewise behaviour and cannot be linearly extrapolated in a wide range. It cannot be modelled effectively using theories and equations. Thus, expert systems have emerged as a major tool for decision-making in such complicated situations (Singh & Raman, 1992).

The conventional method for selecting machining parameters such as cutting speed and feed rate is based on data from machining hand books and/ or on the experience and knowledge of the operator or CNC programmer. The parameters chosen in most cases are extremely conservative to protect over- matching errors from tool failures such as deflection, wear, breakage, etc. Accordingly, the metal removal rate is low due to the use of such conservative machining parameters (Park & Kim, 1998).

Guidelines on machinability data selection is normally made on the basis of the manufacturer's machinability hand book (Hashmi et al., 2003). Using machining data handbook for the choice of cutting conditions for material hardness that lies in the middle of a group is simple and straight forward. But there exists a degree of vagueness in boundary cases, where two choices of cutting speeds are applicable for one choice of material hardness. In this situation, the skilled operator makes a decision on the appropriate cutting speed, based on his experience. However, this method of data selection by individual operators is not very desirable, because it may vary from operator to operator. Therefore, it is desirable to have an operator independent data selection system for choosing machining operation (Hashmi et al., 1998).

While the output variables of the machining process depend on the cutting conditions, the decision concerning the selection of the cutting parameters have an important influence on the extent, cost and quality of the production. Due to the increased use of CNC machines and severe competition between the makers, the importance of precise optimization cutting conditions has increased (Cus & Zuperl, 2006).

Fuzzy logic can be applied to any process in which a human being plays an important role which depends on his subjective assessment (EL Baradie, 1997).
For the selection of machining parameters different methods have been proposed. Hashmi et al. (1998, 1999) applied fuzzy logic with triangular shape for selecting cutting conditions in machining operations using single input (material hardness) and single output (cutting speed) model. El Baradie (1997) presented the development of a fuzzy logic model for machining data selection using material hardness (input) and cutting speed (output) with triangular shape. A study was made by Wong et al (1999) to obtain a generalized model for metal cutting data selection. Wong and Hamouda (2003a) developed an online knowledge-based expert system for machinability data selection using two input-one output model for cutting speed and one input-one output model for feed rate.
Cus and Zuperl (2006) proposed a neural network approach for the optimization of cutting conditions. Neural networks were used by Wong and Hamouda (2003b) in the representation of machinability data to predict optimum machining parameters. Zuperl and Cus (2003) proposed a neural based approach to optimization of cutting parameters to represent the manufacturer's preference structure.
Lee and Tarng (2000) used a polynomial network to construct the relationship between the machining parameters and cutting performance. An optimization algorithm of sequential quadratic programming method was used to solve the optimal machining parameters. A gradient based multi criteria decision making approach was applied by Malakooti and Deviprasad (1989) to aid the decision-maker in setting up machining parameters in metal cutting. The optimal machining parameters for continuous profile machining for turning cylindrical stock were determined by Saravanan et al. (2003) using simulated annealing and genetic algorithm. Vitanov et al. (1995) introduced a knowledge-based interactive approach for optimum machining parameter selection in metal cutting using multi-objective probabilistic geometric programming and artificial techniques. The machining parameters were optimized based on the Taguchi method in a proposed model by Nian et al. (1999) considering the multiple performance characteristics including tool life, cutting force and surface finish.
The fuzzy logic approach is used in different applications. For example, Hashmi et al. (2000) have used the fuzzy logic model to select drilling speeds for different materials in a drilling operation. A fuzzy logic based expert system was developed by Liu at el. (1996) for diagnosing defects in rolling element bearing and offering instructions and guidelines for the detection of these defects. A user friendly fuzzy-expert system was introduced by Yilmaz et al. (2006) for the selection of electro discharge machining process parameters using triangular membership function and expert rules. Arghavani et al. (2001) presented the application of a fuzzy decision support system by applying fuzzy logic theory for gasket selection and gasket sealing performance.
Researchers have applied ANN methods in a wide variety of fields, ranging from science to business and engineering (Ghiassi & Saidene, 2005). Neural networks have the potential to provide some of the human characteristics of problem solving that are difficult to simulate using the logical, analytical techniques of expert system and standard software technologies. The immediate practical implication of neural computing is its emergence as an alternative or supplement to conventional computing systems and AI techniques. As an alternative, neural computing can offer the advantage of execution speed once the network has been

trained. The ability to train the system with data sets, rather than having to write programs, may be more cost effective (Medsker, 1996).
In this chapter the performance of Speed-Feed Fuzzy (SFF) intelligent system is compared with Artificial Neural Networks in finding the selection of machining parameters which can result in a longer tool life, a lower cutting force and better surface finish. The proposed system is expected to contribute in the selection of optimal parameters that will assist process planners, CNC programmers, production engineers and machinists with easy access to data necessary for effective machining process.

2. Fuzzy model for machinability data selection

2.1 Fuzzy logic concept

The fuzzy logic first proposed at 1965 by Lotfi Zadeh(Zadeh, 1965). The fuzzy set theory provides means for representing uncertanity. It is used to model the kind of uncertainity associated with imprecision. It offers the concept to compute a model with words using human expertise used in daily language. The fuzzy set theory provides a mechanism to represent linguistic constructions. The fuzzy inference engine build on a set of rules, so, it is called fuzzy- rule based system. These rules are supplied by an expert or a decsion-maker to formulate the mapping of the system which can perform approximate reasoning similar to but much more primal than that of the human brain (Sivanandam, 2007).

2.2 Fuzziness and fuzzification

In a fuzzy set, the fuzziness is characterized by its membership function. It classifies the element in the set, whether it is discrete or continuous. The membership functions can also be formed by graphical representations. The fuzzification procedure is used to control the fuzziness of the fuzzy set and it is an important concept in the fuzzy logic theory where the crisp quantities are converted to fuzzy quantities (Arghavani et al., 2001; Sivanandam et al., 2007).

2.3 Membership functions for fuzzy variables

The SFF model use multi input- multi output fuzzy variables for the selection of machining parameters (Fig. 1). The multi inputs are material hardness (BHN) and depth of cut (DOC) and the multi outputs are cutting speed and feed rate. The fuzzy expressions for the inputs and outputs are shown in Table 1.
The model is applied for turning operation for wrought carbon steels using different types of tools. The extracted data from Machining Data Handbook (Metcut Research Associates Inc., 1980) are tabulated as shown in Table 2.
Different applications of the fuzzy control technique use a specific shape of the fuzzy set. There is no standard method of choosing the proper shape of the fuzzy sets of the control variables. Trial and error methods are usually exercised (Hashmi et al., 2003). In this model an equal sided triangular shape membership function is selected for both inputs BHN and DOC and for the cutting speed as shown in Figures 2-5. As for the feed rate, an unequal sided triangular shape (Figures 6 - 8) was chosen because of the variation of the feed rate for different values of depth of cut (1-8) mm and 16 mm with their corresponding hardness 85-175 and 175-275 respectively, for the types of cutting tools listed in Table 2.

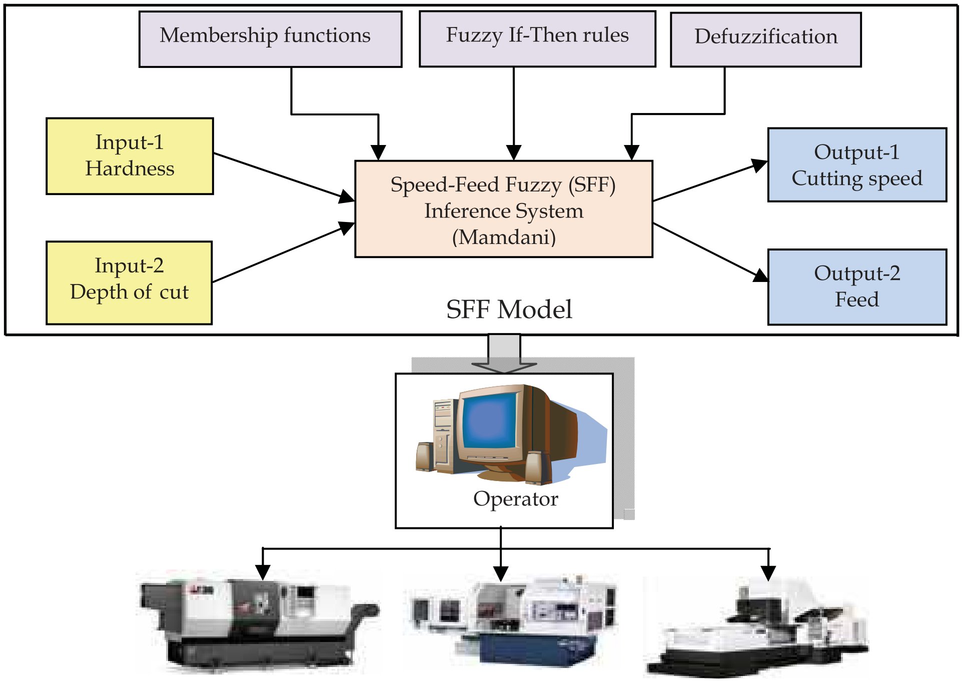

Fig. 1a. Structure of SFF model

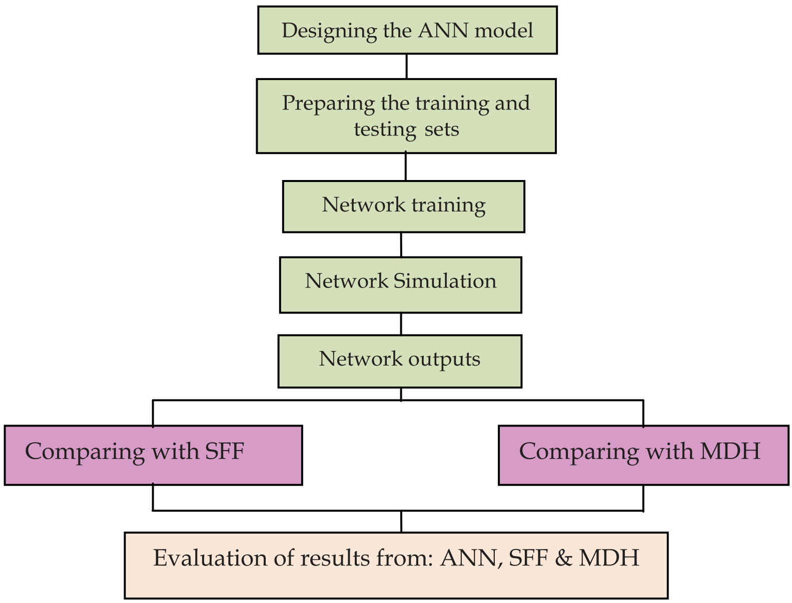

Fig. 1b. Structure of ANN model

Inputs		Outputs	
Material hardness (BHN)	Depth of cut (mm)	Cutting speed (m/min)	Feed rate (mm/rev)
Very soft (VS)	Very shallow (VSH)	Very slow (VSL)	Very slow (VSLO)
Soft (S)	Shallow (SH)	Slow (SL)	Slow (SLO)
Medium (M)	Medium (M)	Medium slow (MSL)	Medium (M)
Medium hard (MH)	Medium deep (MD)	Medium high (MHI)	Medium fast (MFA)
Hard (H)	Deep (D)	High (HI)	Fast (FA)
Very hard (VH)	Very deep (VD)	Very high (VHI)	Very fast (VFA)

Table 1. Fuzzy expressions for inputs and outputs

Condition	Material hardness BHN	Depth of cut mm	High speed steel tool Brazed (S4, S5)		Carbide tool Uncoated Indexible (ISO P10-P40)		Carbide tool Uncoated (ISO P10-P40)		Carbide tool Coated (ISO CP10-CP30)	
			Speed m/min	Feed mm/rev	Speed m/min	Feed mm/rev	Speed m/min	Feed mm/rev	Speed m/min	Feed mm/rev
-Material: Wrought carbon steels.										
Hot rolled	85-125	1	56	0.18	165	0.18	215	0.18	320	0.18
Normalized		4	44	0.40	135	0.50	165	0.50	215	0.40
Annealed		8	35	0.50	105	0.75	130	0.75	170	0.50
Cold drawn		16	27	0.75	81	1.00	100	1.00	-	-
Hot rolled	125-175	1	46	0.18	150	0.18	195	0.18	290	0.18
Normalized		4	38	0.40	125	0.50	150	0.50	190	0.40
Annealed		8	30	0.50	100	0.75	120	0.75	150	0.50
Cold drawn		16	24	0.75	75	1.00	95	1.00	-	-
Hot rolled	175-225	1	44	0.18	140	0.18	175	0.18	260	0.18
Normalized		4	35	0.40	115	0.50	135	0.50	170	0.40
Annealed		8	29	0.50	90	0.75	100	0.75	135	0.50
Cold drawn		16	23	1.00	72	1.00	81	1.00	-	-
Hot rolled	225-275	1	38	0.18	125	0.18	155	0.18	230	0.18
Normalized		4	29	0.40	110	0.50	120	0.50	150	0.40
Annealed		8	23	0.50	87	0.75	95	0.75	120	0.50
Cold drawn		16	18	1.00	67	1.00	73	1.00	-	-

Table 2. Machining parameters for workpiece-tool combination, turning process.

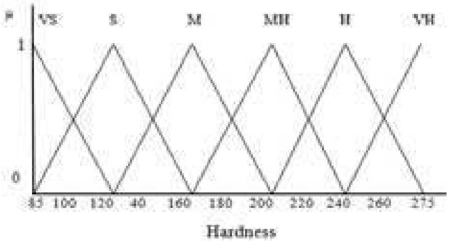

Fig. 2. Hardness membership function

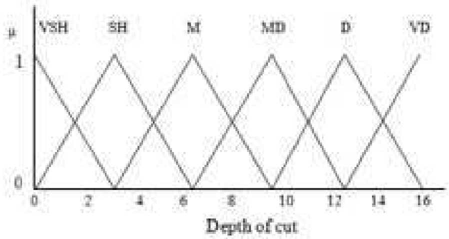

Fig. 3. Depth of cut membership function

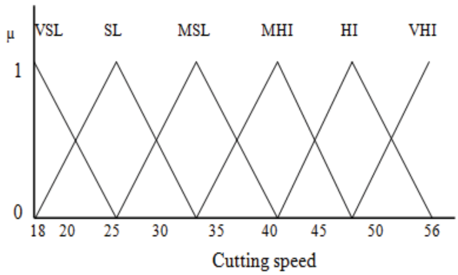

Fig. 4. Speed membership function for HSS tool

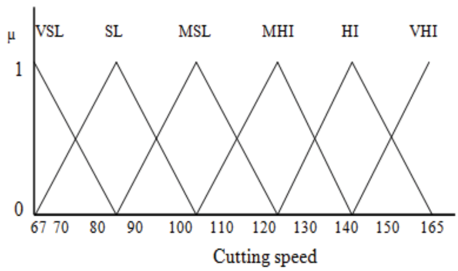

Fig. 5. Speed membership function for carbide tool

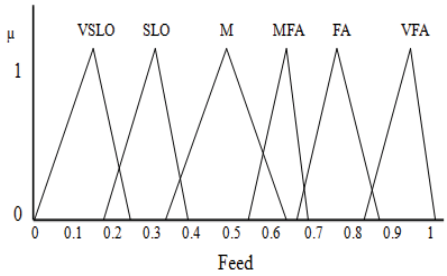

Fig. 6. Feed membership function (BHN=85-175,HSS)

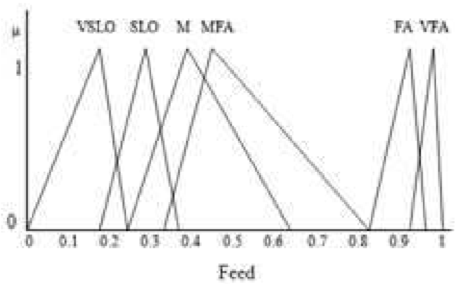

Fig. 7. Feed membership function (BHN=175-275, HSS)

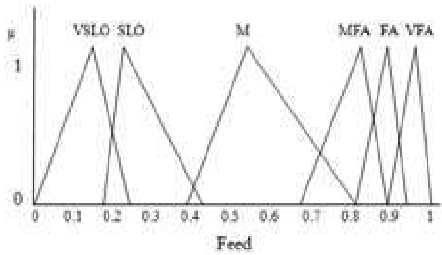

Fig. 8. Feed membership function for carbide tool

2.4 Fuzzy rules

The point of fuzzy logic is to map an input space to an output space and the primary mechanism for doing this is a set of IF-THEN rules with the application of fuzzy operator AND or OR. These if-then rules are used to formulate the conditional statements that comprise fuzzy logic. By using the rules, then the fuzzy inference system (FIS) formulates the mapping form. Mamdani's fuzzy inference system, which is used in this work, is the most commonly seen fuzzy methodology (The MathWorks, Inc., 2009). The relationship between the input variables and output variables is characterized by if-then rules defined based on experimental, expert and engineering knowledge (Yilmaz et al., 2006). The two common methods for the FIS engine are Max-Min method and Max-Product method. The difference between them is the aggregation of the rules. The first use truncation and the last use multiplication of the output fuzzy set. Both methods are tested and the Max-Min method gives more accurate results, therefore, it is used in all calculations in the fuzzy system.

In this study, there are two input variables hardness and depth of cut each of six fuzzy sets, and then the fuzzy system of a minimum of 6 x 6 = 36 rules can be defined. Table 3 shows a part of the rules in linguistic form. By using these rules the input-output variables in a network representation can be drawn as in Figs. 9 and 10.

Rule 1: IF hardness is very soft AND depth of cut is very shallow THEN speed is very high and feed is very slow.
Rule 2: IF hardness is very soft AND depth of cut is shallow THEN speed is very high and feed is slow.
Rule 3: IF hardness is very soft AND depth of cut is medium THEN speed is medium high and feed is medium.
Rule 4: IF hardness is very soft AND depth of cut is medium deep THEN speed is medium slow and feed is medium.
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Rule 35: IF hardness is very hard AND depth of cut is deep THEN speed is very slow and feed is very fast.
Rule 36: IF hardness is very hard AND depth of cut is very deep THEN speed is very slow and very fast.

Table 3. Part of fuzzy rules in linguistic form.

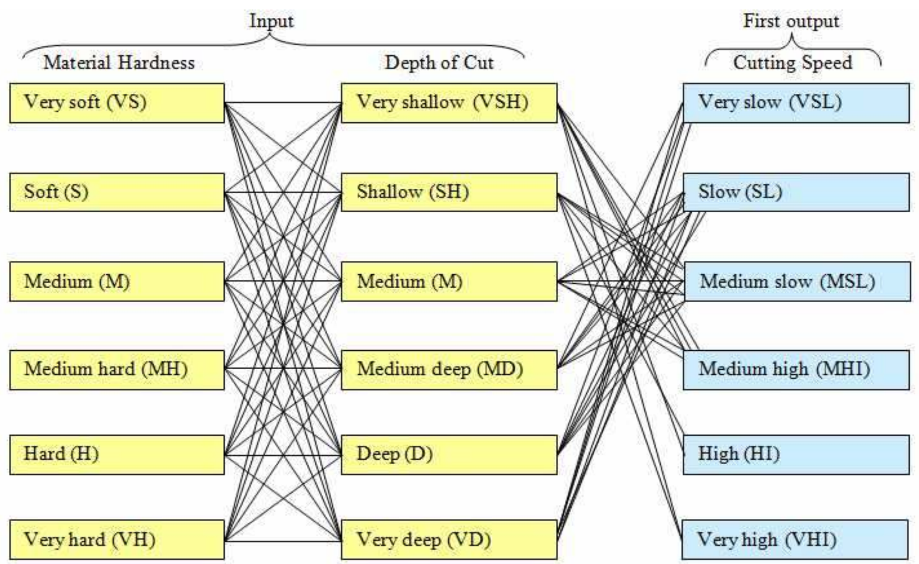


Fig. 9. Network representation for the first output- cutting speed.

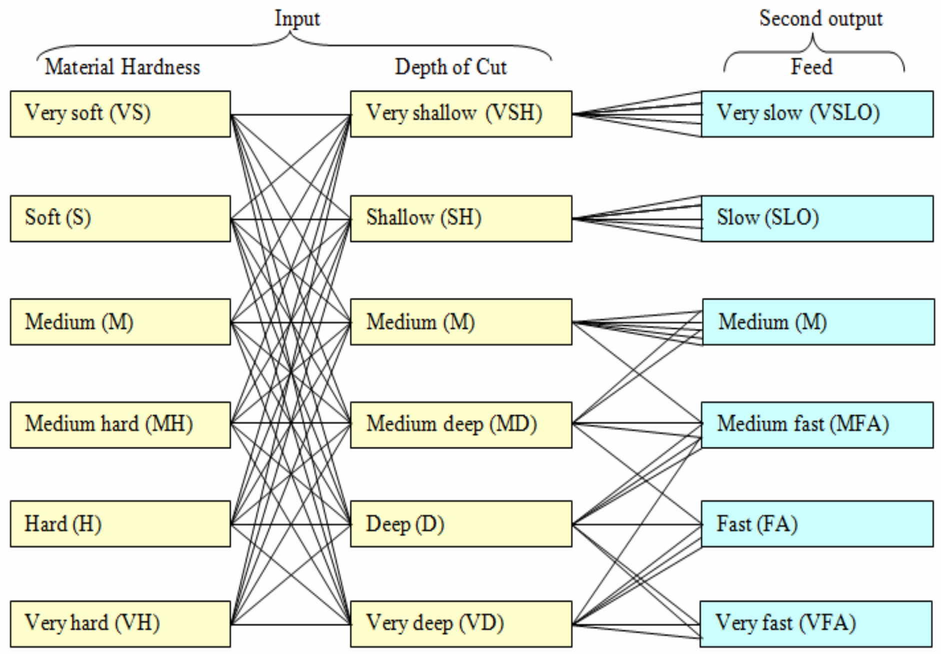


Fig. 10. Network representation for the second output- feed.

2.5 Defuzzification

Defuzzification is the process of converting the fuzzy quantities to crisp quantities. There are several methods used for defuzzifying the fuzzy output functions: the centroid method, the centre of sums, the centre of largest area, the max-membership function, the mean-max membership function, the weighted average method, and the first of maxima or the last of maxima. The selected defuzzification method is significantly affecting the accuracy and speed of the fuzzy algorithm. The centroid method provides more linear results by taking the union of the output of each fuzzy rule (Arghavani et al., 2001; Sivanandam et al., 2007) and this method is adopted in this study.

3. Artificial Neural Network (ANN) model

Neural networks attempt to model human intuition by simulating the physical process upon which intuition is based, that is, by simulating the process of adaptive biological learning. It learns through experience, and is able to continue learning as the problem environment changes (Kim & Park, 1997).

A typical ANN is comprised of several layers of interconnected neurons, each of which is connected to other neurons in the ensuing layer. Data is presented to the neural network via an input layer, while an output layer holds the response of the network to the input. One or more hidden layers may exist between the input layer and the output layer. All hidden and output neurons process their inputs by multiplying each input by its weight, summing the product, and then processing the sum using a non-linear transfer function to generate a result (Chau, 2006).

The most commonly used approach to ANN learning is the feed-forward back propagation algorithm. The parameters of the model such as the choice of input nodes, number of hidden layers, number of hidden nodes (in each hidden layer), and the form of transfer functions, are problem dependent and often require trial and error to find the best model for a particular application (Ghiassi & Saidene, 2005).

There is no exact rule to decide the number of the hidden layers. There are four methods of selecting the number of hidden nodes (NHN) (Kuo et al., 2002; Yazgan et al., 2009). The four methods are dependent on: the number of input nodes (IN), the number of output nodes (ON), and the number of samples (SN):

$$\text{NHN 1} = (\text{IN x ON})^{1/2} \tag{1}$$

$$\text{NHN 2} = ½\,(\text{IN + ON}) \tag{2}$$

$$\text{NHN 3} = ½\,(\text{IN + ON}) + (\text{SN})^{1/2} \tag{3}$$

$$\text{NHN 4} = 2\,(\text{IN}) \tag{4}$$

The ANN in this study (Fig.11) uses feed-forward back-propagation algorithm. It is composed of two neurons for the two inputs material hardness and depth of cut. The outputs from the neural network are speed and feed; therefore two output neurons are required.

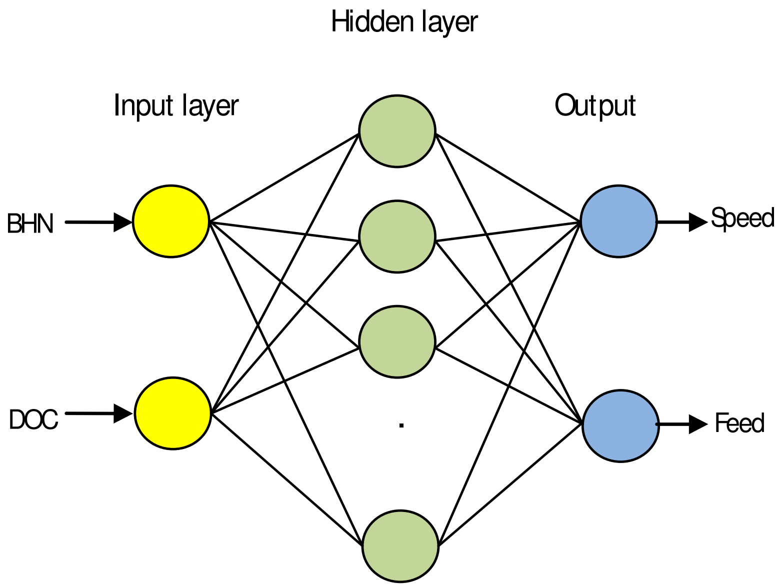


Fig. 11. Neural network structure for machining parameters

4. Results and discussion

Both SFF-ANN are used to predict optimum machining parameters using data extracted from the Machining Data Handbook (MDH) (Table 2).
A user-friendly viewer of the SFF model is shown in Fig. 12 enabling an easy and time saving way for operator for interring the inputs and getting the outputs.

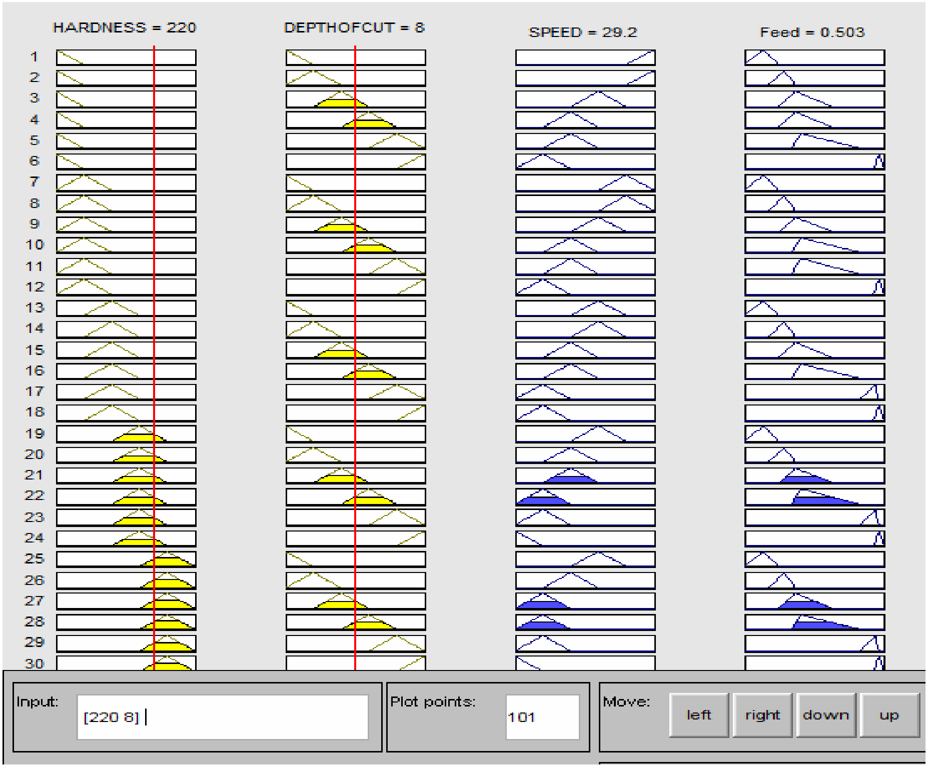


Fig. 12. User-friendly viewer for the SFF model (from MATLAB)

The viewer shown in Fig.12 is used to generate the input-output samples. The values are tabulated in Tables 4 and 5. The tables show the validation of the predicted values of cutting speed and feed found by the SFF model with the Machining Data Handbook. Seventy two different values of wrought carbon steel hardness from (85-275) BHN and depth of cut from (1-16) mm were selected for this comparison. For demonstration purpose two tool types are used: high speed steel (HSS) tool and uncoated brazed carbide (Carbide) tool. The SFF model is applied to obtain the outputs speed and feed and the values are then compared. The absolute error percentage is calculated for each value and the mean absolute error percentages are obtained for the 36 samples. The mean error percentage is almost 7% for speed and 4% for feed when using high speed steel tool and for carbide tool is almost 8% for speed and 7% for feed (Table 6). In order to get better results, the density of the selected samples can be increased.

No.	Material hardness (BHN)	Depth of cut (mm)	Cutting speed (m/min) MDH (Table 2)	SFF model	Abs. error (%)	Feed (mm/rev) MDH (Table 2)	SFF model	Abs. error (%)
1	85	1	56	53.4	4.6429	0.18	0.171	5.0000
2	85	4	44	47.5	7.9545	0.4	0.361	9.7500
3	85	8	35	37	5.7143	0.5	0.4680	6.4000
4	85	16	27	25.6	5.1852	0.75	0.7540	0.5333
5	105	1	56	49.3	11.9643	0.18	0.1760	2.2222
6	105	4	44	46.8	6.3636	0.4	0.37	7.5000
7	105	8	35	37	5.7143	0.5	0.5050	1.0000
8	105	16	27	25.6	5.1852	0.75	0.7550	0.6667
9	120	1	56	48.4	13.5714	0.18	0.171	5.0000
10	120	4	44	46.2	5.0000	0.4	0.3610	9.7500
11	120	8	35	37	5.7143	0.5	0.5050	1.0000
12	120	16	27	25.6	5.1852	0.75	0.7540	0.5333
13	145	1	46	44.1	4.1304	0.18	0.1740	3.3333
14	145	4	38	41.8	10.0000	0.4	0.3670	8.2500
15	145	8	30	32.8	9.3333	0.5	0.5010	0.2000
16	145	16	24	25.6	6.6667	0.75	0.7550	0.6667
17	180	1	44	37.8	14.0909	0.18	0.1770	1.6667
18	180	4	35	37	5.7143	0.4	0.3680	8.0000
19	180	8	29	29.4	1.3793	0.5	0.5030	0.6000
20	180	16	23	24.6	6.9565	1	0.9630	3.7000
21	190	1	44	38.2	13.1818	0.18	0.1710	5.0000
22	190	4	35	35.3	0.8571	0.4	0.3580	10.5000
23	190	8	29	29.4	1.3793	0.5	0.5030	0.6000
24	190	16	23	23.1	0.4348	1	0.9630	3.7000
25	220	1	44	37.9	13.8636	0.18	0.1750	2.7778
26	220	4	35	30.7	12.2857	0.4	0.3650	8.7500
27	220	8	29	29.2	0.6897	0.5	0.5030	0.6000
28	220	16	23	20.8	9.5652	1	0.9630	3.7000
29	245	1	38	38.2	0.5263	0.18	0.1710	5.0000
30	245	4	29	31	6.8966	0.4	0.3580	10.5000
31	245	8	23	25.3	10.0000	0.5	0.5030	0.6000
32	245	16	18	20.5	13.8889	1	0.9630	3.7000
33	265	1	38	35.5	6.5789	0.18	0.1710	5.0000
34	265	4	29	31	6.8966	0.4	0.3580	10.5000
35	265	8	23	24.6	6.9565	0.5	0.5030	0.6000
36	265	16	18	20.6	14.4444	1	0.9630	3.7000

Table 4. Comparison of the results from SFF model with MDH for high speed steel tool

No.	Material hardness (BHN)	Depth of cut (mm)	Cutting speed (m/min) MDH (Table 2)	SFF model	Abs. error (%)	Feed (mm/rev) MDH (Table 2)	SFF model	Abs. error (%)
1	95	1	165	151	8.4848	0.18	0.1700	5.5556
2	95	4	135	143	5.9259	0.5	0.4200	16.000
3	95	8	105	116	10.4762	0.75	0.6750	10.000
4	95	16	81	86.6	6.9136	1	0.9510	4.9000
5	110	1	165	147	10.9091	0.18	0.1710	5.0000
6	110	4	135	141	4.4444	0.5	0.4260	14.800
7	110	8	105	118	12.3810	0.75	0.6750	10.000
8	110	16	81	86.6	6.9136	1	0.9500	5.0000
9	140	1	150	136	9.3333	0.18	0.1760	2.2222
10	140	4	125	130	4.0000	0.5	0.4370	12.600
11	140	8	100	116	16.000	0.75	0.6750	10.000
12	140	16	75	86.6	15.4667	1	0.9490	5.1000
13	195	1	140	119	15.000	0.18	0.1700	5.5556
14	195	4	115	109	5.2174	0.5	0.4200	16.000
15	195	8	90	96.4	7.1111	0.75	0.6750	10.000
16	195	16	72	77	6.9444	1	0.9520	4.8000
17	210	1	140	119	15.000	0.18	0.1700	5.5556
18	210	4	115	100	13.0435	0.5	0.4650	7.0000
19	210	8	90	96.4	7.1111	0.75	0.6980	6.9333
20	210	16	72	73.7	2.3611	1	0.9510	4.9000
21	230	1	125	119	4.8000	0.18	0.17	5.5556
22	230	4	110	101	8.1818	0.5	0.4510	9.8000
23	230	8	87	92	5.7471	0.75	0.7510	0.1333
24	230	16	67	73.4	9.5522	1	0.9510	4.9000
25	240	1	125	119	4.8000	0.18	0.1700	5.5556
26	240	4	110	101	8.1818	0.5	0.4320	13.600
27	240	8	87	86.5	0.5747	0.75	0.7870	4.9333
28	240	16	67	73.3	9.4030	1	0.9520	4.8000
29	255	1	125	116	7.2000	0.18	0.1770	1.6667
30	255	4	110	99.6	9.4545	0.5	0.4840	3.2000
31	255	8	87	84.2	3.2184	0.75	0.7120	5.0667
32	255	16	67	74.3	10.8955	1	0.9480	5.2000
33	270	1	125	110	12.000	0.18	0.1700	5.5556
34	270	4	110	101	8.1818	0.5	0.4420	11.600
35	270	8	87	84	3.4483	0.75	0.6870	8.4000
36	270	16	67	73.3	9.4030	1	0.9520	4.8000

Table 5. Comparison of the results from SFF model with MDH for carbide tool

Mean absolute error percentage (Using HSS tool)
-Speed= 7.19%
-Feed= 4.19%
Mean absolute error percentage (Using carbide tool)
-Speed= 8.29%
-Feed= 7.13%

Table 6. Mean absolute error using 36 samples

Figures 13-16 show the results from Tables 4 and 5 in graphical representation. From these figures it can be seen that the fuzzy cutting speed and feed obtained by the SFF model lie close to the recommended values from the Machining Data Handbook.

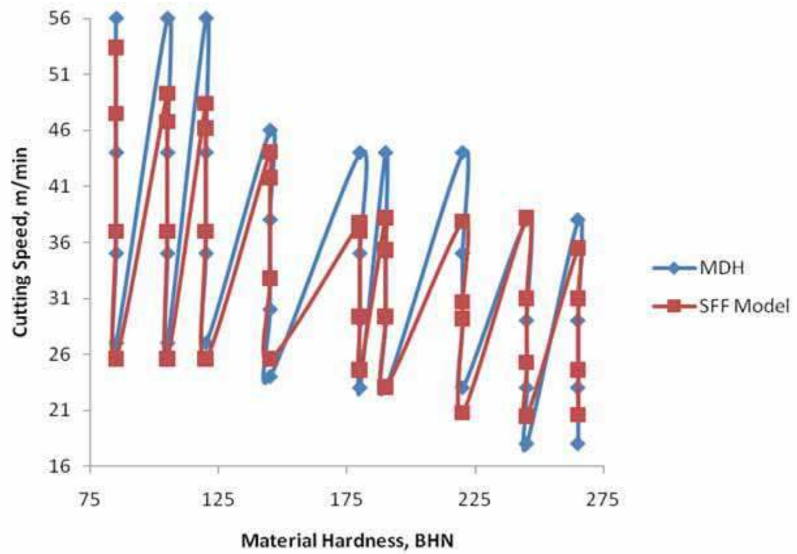


Fig. 13. Cutting speed for high speed steel

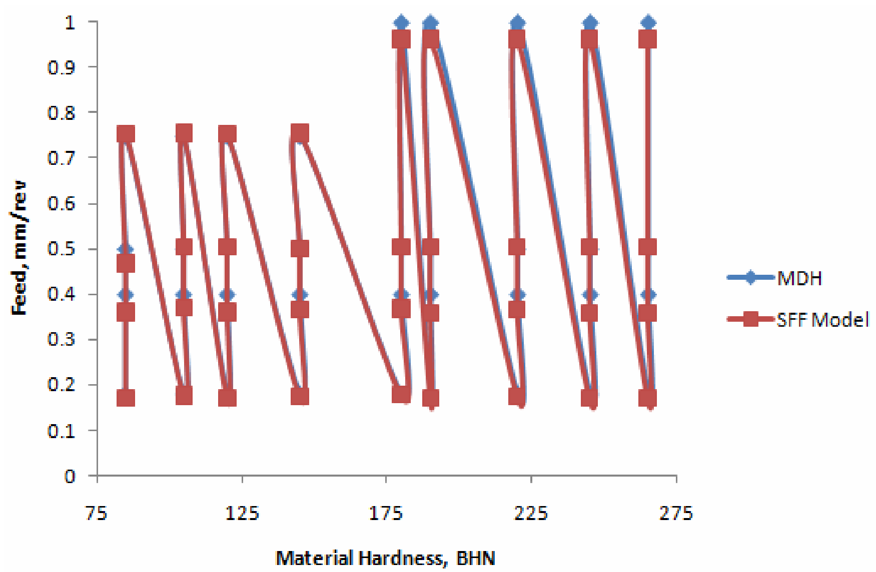


Fig. 14. Feed for high speed steel

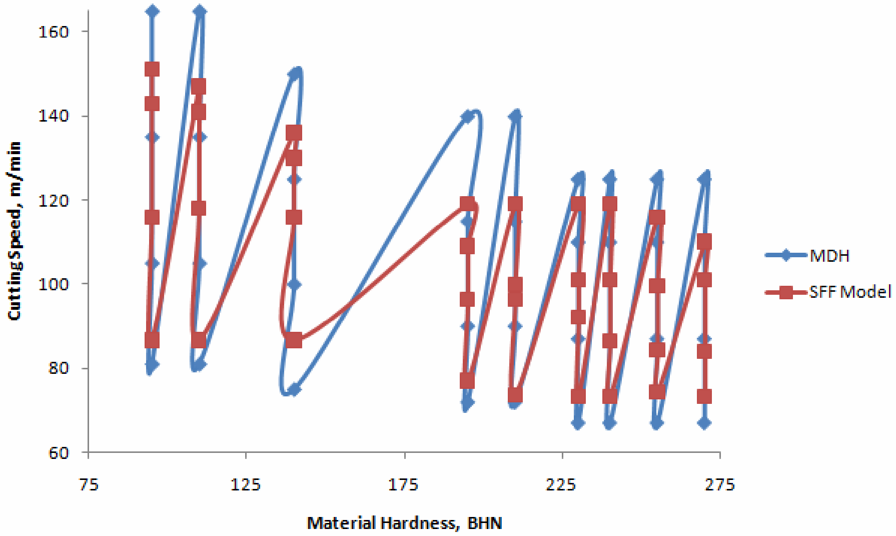


Fig. 15. Cutting speed for carbide tool

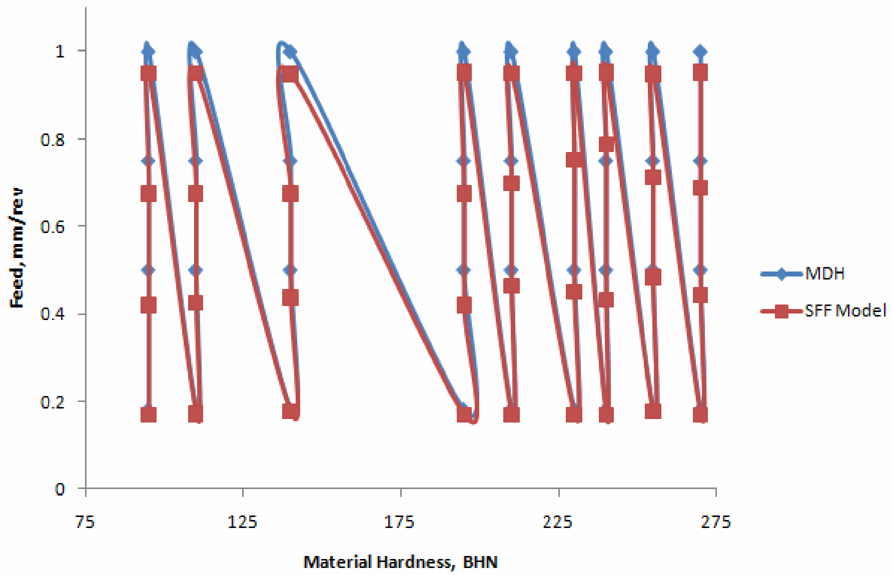


Fig. 16. Feed for carbide tool

The ANN model is composed of two input neurons, material hardness and depth of cut, and two output neurons speed and feed. The values of inputs and outputs are not of the same scale. So, all data are normalized. Tables 7 and 8 contain a set of 18 training and 18 testing samples in normalized form for HSS tool and Carbide tool respectively.

No.	Input 1 Hardness	Input 2 Depth of cut	Output 1 Speed	Output 2 Feed	No.	Input 1 Hardness	Input 2 Depth of cut	Output 1 Speed	Output 2 Feed
Training set					Testing set				
1	0.0137	0.0038	0.0436	0.0100	19	0.0289	0.0307	0.0240	0.0293
2	0.0137	0.0153	0.0388	0.0210	20	0.0289	0.0613	0.0201	0.0562
3	0.0137	0.0307	0.0302	0.0273	21	0.0305	0.0038	0.0312	0.0100
4	0.0137	0.0613	0.0209	0.0440	22	0.0305	0.0153	0.0288	0.0209
5	0.0169	0.0038	0.0403	0.0103	23	0.0305	0.0307	0.0240	0.0293
6	0.0169	0.0153	0.0382	0.0216	24	0.0305	0.0613	0.0189	0.0562
7	0.0169	0.0307	0.0302	0.0294	25	0.0354	0.0038	0.0310	0.0102
8	0.0169	0.0613	0.0209	0.0440	26	0.0354	0.0153	0.0251	0.0213
9	0.0193	0.0038	0.0395	0.0100	27	0.0354	0.0307	0.0239	0.0293
10	0.0193	0.0153	0.0378	0.0210	28	0.0354	0.0613	0.0170	0.0562
11	0.0193	0.0307	0.0302	0.0294	29	0.0394	0.0038	0.0312	0.0100
12	0.0193	0.0613	0.0209	0.0440	30	0.0394	0.0153	0.0253	0.0209
13	0.0233	0.0038	0.0360	0.0101	31	0.0394	0.0307	0.0207	0.0293
14	0.0233	0.0153	0.0342	0.0214	32	0.0394	0.0613	0.0168	0.0562
15	0.0233	0.0307	0.0268	0.0292	33	0.0426	0.0038	0.0290	0.0100
16	0.0233	0.0613	0.0209	0.0440	34	0.0426	0.0153	0.0253	0.0209
17	0.0289	0.0038	0.0309	0.0103	35	0.0426	0.0307	0.0201	0.0293
18	0.0289	0.0153	0.0302	0.0215	36	0.0426	0.0613	0.0168	0.0562

Table 7. Training-testing data for high speed steel tool

No.	Input 1 Hardness	Input 2 Depth of cut	Output 1 Speed	Output 2 Feed	No.	Input 1 Hardness	Input 2 Depth of cut	Output 1 Speed	Output 2 Feed
Training set					Testing set				
1	0.0136	0.0038	0.0402	0.0083	19	0.0301	0.0307	0.0257	0.0342
2	0.0136	0.0153	0.0381	0.0206	20	0.0301	0.0613	0.0196	0.0466
3	0.0136	0.0307	0.0309	0.0331	21	0.0330	0.0038	0.0317	0.0083
4	0.0136	0.0613	0.0231	0.0466	22	0.0330	0.0153	0.0269	0.0221
5	0.0158	0.0038	0.0391	0.0084	23	0.0330	0.0307	0.0245	0.0368
6	0.0158	0.0153	0.0375	0.0209	24	0.0330	0.0613	0.0195	0.0466
7	0.0158	0.0307	0.0314	0.0331	25	0.0344	0.0038	0.0317	0.0083
8	0.0158	0.0613	0.0231	0.0465	26	0.0344	0.0153	0.0269	0.0212
9	0.0201	0.0038	0.0362	0.0086	27	0.0344	0.0307	0.0230	0.0386
10	0.0201	0.0153	0.0346	0.0214	28	0.0344	0.0613	0.0195	0.0466
11	0.0201	0.0307	0.0309	0.0331	29	0.0365	0.0038	0.0309	0.0087
12	0.0201	0.0613	0.0231	0.0465	30	0.0365	0.0153	0.0265	0.0237
13	0.0279	0.0038	0.0317	0.0083	31	0.0365	0.0307	0.0224	0.0349
14	0.0279	0.0153	0.0290	0.0206	32	0.0365	0.0613	0.0198	0.0464
15	0.0279	0.0307	0.0257	0.0331	33	0.0387	0.0038	0.0293	0.0083
16	0.0279	0.0613	0.0205	0.0466	34	0.0387	0.0153	0.0269	0.0217
17	0.0301	0.0038	0.0317	0.0083	35	0.0387	0.0307	0.0224	0.0337
18	0.0301	0.0153	0.0266	0.0228	36	0.0387	0.0613	0.0195	0.0466

Table 8. Training-testing data for carbide tool

The first half of the data in each table is used for training the network with different number of hidden nodes: two, four, and eight, extracted using the equations (1-4). The models are trained with different training parameters and different activation functions as shown in Tables 9 and 10. The mean square error (MSE) value is used as the stop criteria.

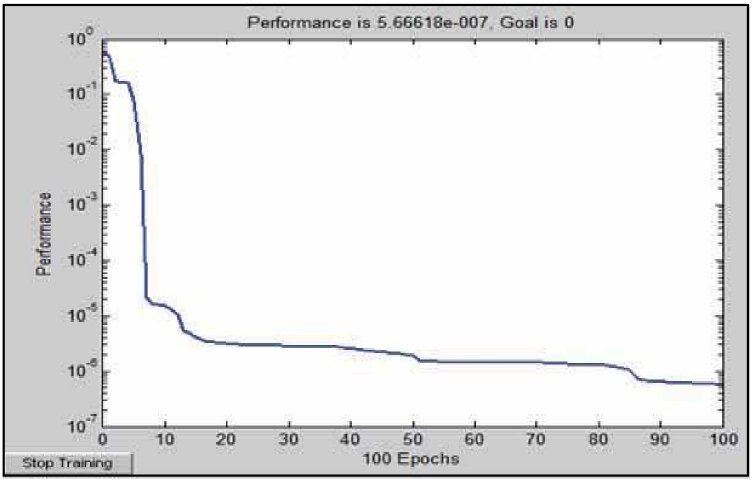
Input Nodes	Hidden Nodes	Output Nodes	Training Function	Transfer Function	Epochs	Performance
2	2	2	TRAINLIM	TANSIG	150	3.61807e-006
2	4	2	TRAINLIM	TANSIG	150	3.43611e-006
2	8	2	TRAINLIM	TANSIG	100	5.66618e-007
2	2	2	TRAINLIM	SIGMOID	200	3.23253e-006
2	4	2	TRAINLIM	SIGMOID	350	3.78049e-007
2	8	2	TRAINLIM	SIGMOID	350	3.117 65e-007

Table 9. ANN model parameters for HSS tool

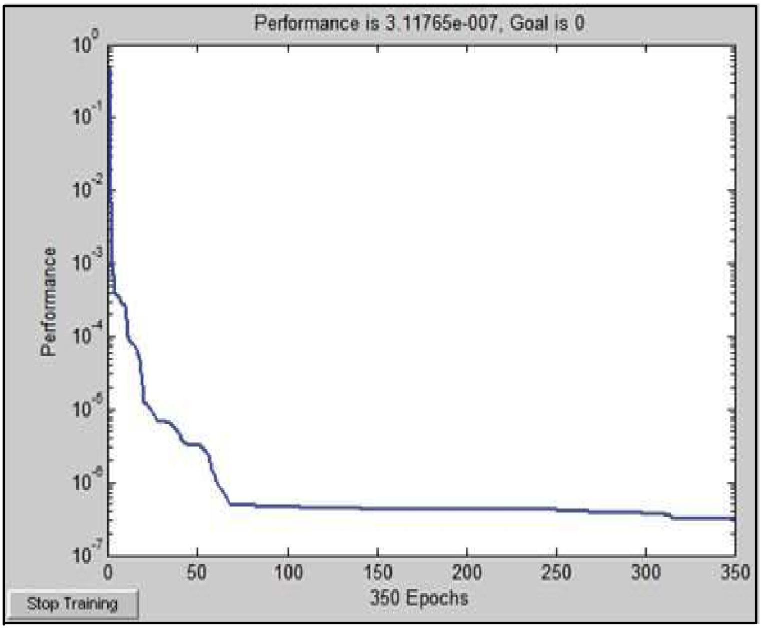
Input Nodes	Hidden Nodes	Output Nodes	Training Function	Transfer Function	Epochs	Performance
2	2	2	TRAINLIM	TANSIG	350	9.96923e-007
2	4	2	TRAINLIM	TANSIG	250	8.26549e-007
2	8	2	TRAINLIM	TANSIG	190	2.19803e-007
2	2	2	TRAINLIM	SIGMOID	250	9.87903e-007
2	4	2	TRAINLIM	SIGMOID	236	5.12694e-007
2	8	2	TRAINLIM	SIGMOID	145	1.325 60e-007

Table 10. ANN model parameters for carbide tool.

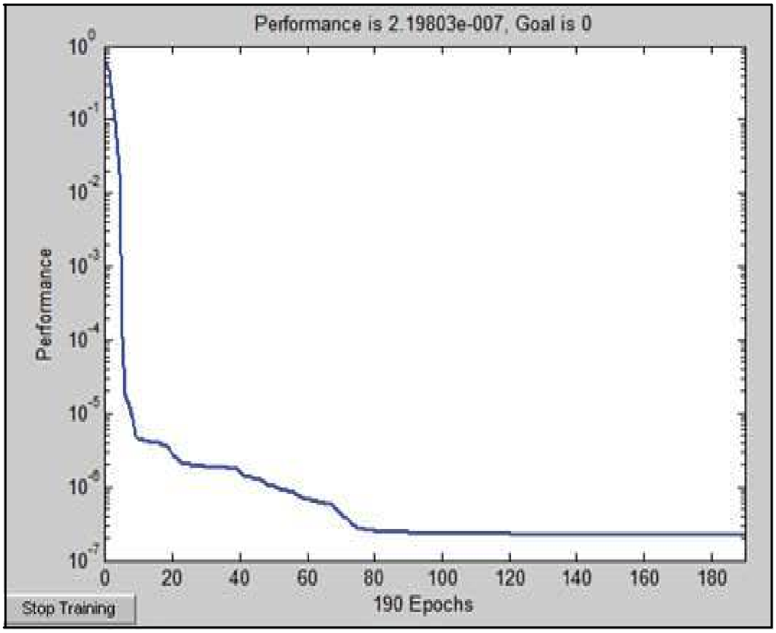
The trained neural network was tested based on the second half of the input-output samples in Tables 7 and 8. The performance of the best training processes is shown in Fig.17. Fig.18 shows the architecture of the best feed forward neural network (2-8-2) model.



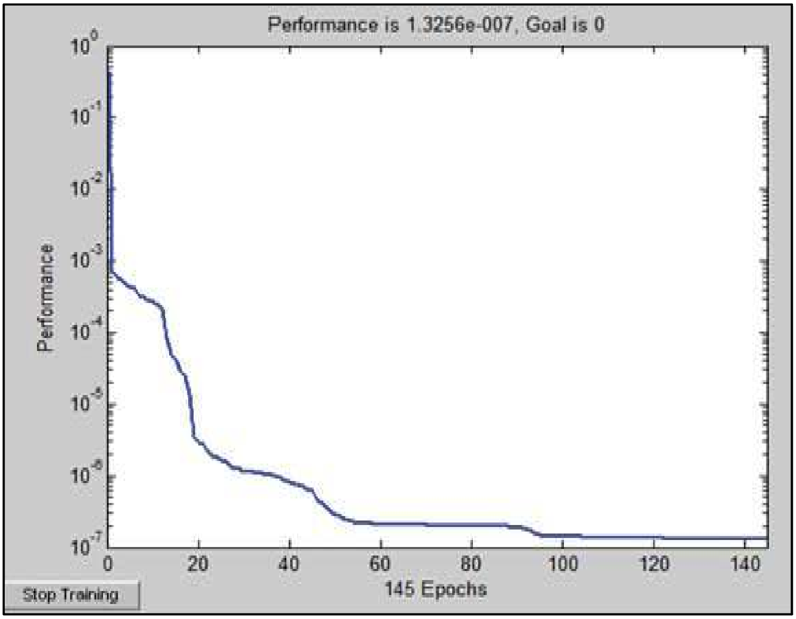
(a) 2-8-2 ANN model using Tansig function for HSS tool



(b) 2-8-2 ANN model using Sigmoid function for HSS tool



(c) 2-8-2 ANN model using Tansig function for carbide tool



(d) 2-8-2 ANN model using Sigmoid function for carbide tool

Fig. 17. Performance curves for best tested ANN models

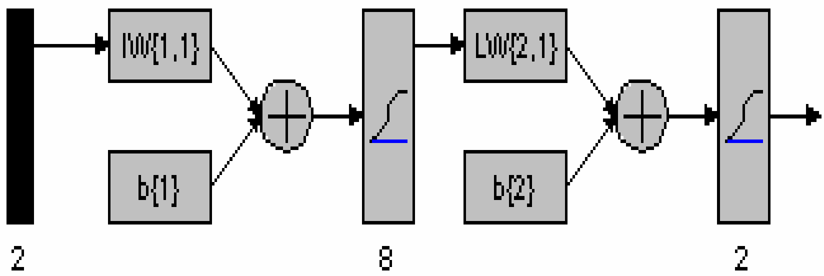


Fig. 18. Architecture of 2-8-2 ANN model (from MATLAB)

From Tables 9 and 10 and Fig.17 (b) and (d), it can be seen that the 2-8-2 ANN model gives a small error. The error is 3.11765e-007 for high speed steel and 1.3256e-007 for carbide tool and the trained network is considered valid.

The ANN model is simulated based on the test data set (19-36) from Tables 7 and 8. The outputs from the network simulation are shown in Tables 11 and 12. These tables show the comparison between the values obtained by SFF and the values predicted by ANN for the two types of the tools used in the demonstration. From the tables it can be seen that the obtained values closely matches the predicted values of the ANN model.

	Output- Speed			Output- Feed		
No.	SFF model	ANN model	Difference	SFF model	ANN model	Difference
19	0.0239	0.0240	0.0001	0.0293	0.0293	0
20	0.0199	0.0201	0.0002	0.0561	0.0562	0.0001
21	0.0310	0.0312	0.0002	0.0100	0.0100	0
22	0.0287	0.0288	0.0001	0.0212	0.0209	-0.0003
23	0.0233	0.0240	0.0007	0.0294	0.0293	-0.0001
24	0.0192	0.0189	-0.0003	0.0562	0.0562	0
25	0.0302	0.0310	0.0008	0.0101	0.0102	0.0001
26	0.0277	0.0251	-0.0026	0.0207	0.0213	0.0006
27	0.0225	0.0239	0.0014	0.0293	0.0293	0
28	0.0169	0.0170	0.0001	0.0564	0.0562	-0.0002
29	0.0297	0.0312	0.0015	0.0102	0.0100	-0.0002
30	0.0268	0.0253	0.0015	0.0204	0.0209	0.0005
31	0.0210	0.0207	-0.0003	0.0293	0.0293	0
32	0.0166	0.0168	0.0002	0.0560	0.0562	0.0002
33	0.0291	0.0290	-0.0001	0.0104	0.0100	-0.0004
34	0.0248	0.0253	0.0005	0.0209	0.0209	0
35	0.0202	0.0201	-0.0001	0.0293	0.0293	0
36	0.0165	0.0168	0.0003	0.0561	0.0562	0.0001

Table 11. Comparison of outputs for HSS tool

	Output- Speed			Output- Feed		
No.	SFF model	ANN model	Difference	SFF model	ANN model	Difference
19	0.0257	0.0255	0.0002	0.0342	0.0340	0.0002
20	0.0196	0.0196	0	0.0466	0.0466	0
21	0.0317	0.0314	0.0003	0.0083	0.0084	-0.0001
22	0.0269	0.0269	0	0.0221	0.0221	0
23	0.0245	0.0239	0.0006	0.0368	0.0365	0.0003
24	0.0195	0.0196	-0.0001	0.0466	0.0466	0
25	0.0317	0.0310	0.0007	0.0083	0.0084	-0.0001
26	0.0269	0.0267	0.0002	0.0212	0.0224	-0.0012
27	0.0230	0.0228	0.0002	0.0386	0.0385	0.0001
28	0.0195	0.0196	-0.0001	0.0466	0.0465	0.0001
29	0.0309	0.0305	0.0004	0.0087	0.0083	0.0004
30	0.0265	0.0264	0.0001	0.0237	0.0227	0.001
31	0.0224	0.0226	-0.0002	0.0349	0.0349	0
32	0.0198	0.0196	0.0002	0.0464	0.0465	-0.0001
33	0.0293	0.0299	-0.0006	0.0083	0.0082	0.0001
34	0.0269	0.0267	0.0002	0.0217	0.0216	0.0001
35	0.0224	0.0222	0.0002	0.0337	0.0336	0.0001
36	0.0195	0.0195	0	0.0466	0.0465	0.0001

Table 12. Comparison of outputs for carbide tool

No.	Input 1 Hardness	Input 2 Depth of cut	Output 1 Speed	Output 2 Feed	No.	Input 1 Hardness	Input 2 Depth of cut	Output 1 Speed	Output 2 Feed
Training set					Testing set				
1	0.0136	0.0038	0.0454	0.0102	19	0.0301	0.0307	0.0235	0.0282
2	0.0136	0.0153	0.0357	0.0226	20	0.0301	0.0613	0.0187	0.0564
3	0.0136	0.0307	0.0284	0.0282	21	0.0330	0.0038	0.0357	0.0102
4	0.0136	0.0613	0.0219	0.0423	22	0.0330	0.0153	0.0284	0.0226
5	0.0158	0.0038	0.0454	0.0102	23	0.0330	0.0307	0.0235	0.0282
6	0.0158	0.0153	0.0357	0.0226	24	0.0330	0.0613	0.0187	0.0564
7	0.0158	0.0307	0.0284	0.0282	25	0.0344	0.0038	0.0357	0.0102
8	0.0158	0.0613	0.0219	0.0423	26	0.0344	0.0153	0.0284	0.0226
9	0.0201	0.0038	0.0454	0.0102	27	0.0344	0.0307	0.0235	0.0282
10	0.0201	0.0153	0.0357	0.0226	28	0.0344	0.0613	0.0187	0.0564
11	0.0201	0.0307	0.0284	0.0282	29	0.0365	0.0038	0.0308	0.0102
12	0.0201	0.0613	0.0219	0.0423	30	0.0365	0.0153	0.0235	0.0226
13	0.0279	0.0038	0.0373	0.0102	31	0.0365	0.0307	0.0187	0.0282
14	0.0279	0.0153	0.0308	0.0226	32	0.0365	0.0613	0.0146	0.0564
15	0.0279	0.0307	0.0243	0.0282	33	0.0387	0.0038	0.0308	0.0102
16	0.0279	0.0613	0.0195	0.0423	34	0.0387	0.0153	0.0235	0.0226
17	0.0301	0.0038	0.0357	0.0102	35	0.0387	0.0307	0.0187	0.0282
18	0.0301	0.0153	0.0284	0.0226	36	0.0387	0.0613	0.0146	0.0564

Table 13. Training-testing data from MDH for high speed steel tool

The performance of the SFF is compared with ANN and MDH using high speed steel tool as a demonstration example (Table 13).
The performance of the best training process using network architecture 2-8-2 with 950 epochs is shown in Fig. 19 where the value is 3.92694e-007.

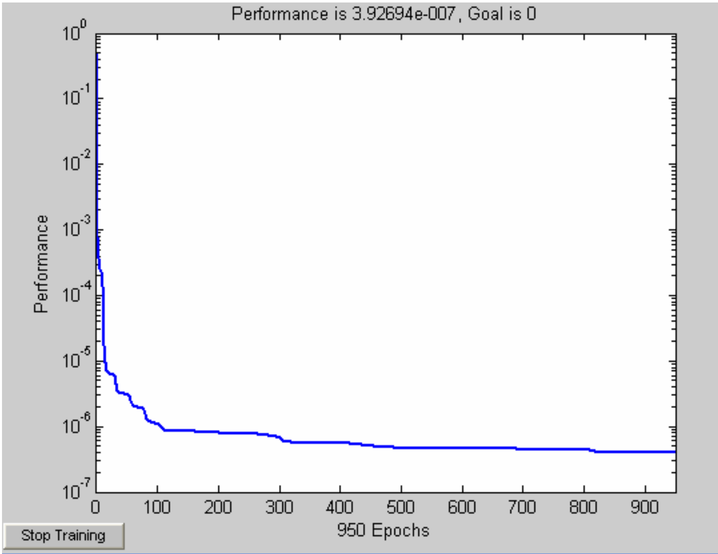


Fig. 19. Performance curve for best tested ANN model

The output from the simulated network using test data set (19-36) from Table 13 is shown in Figures 20 and 21. The Figures show the comparison between the values obtained by SFF model and the predicted values by ANN model and values from MDH.

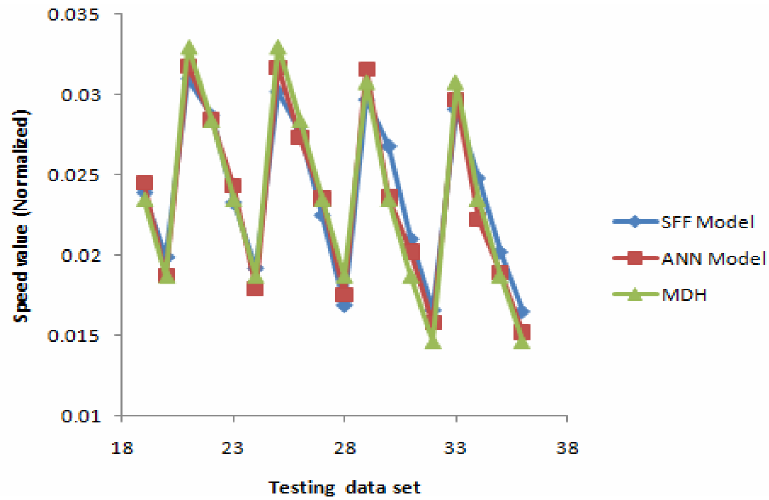


Fig. 20. Comparison of speed values between SFF, ANN and MDH

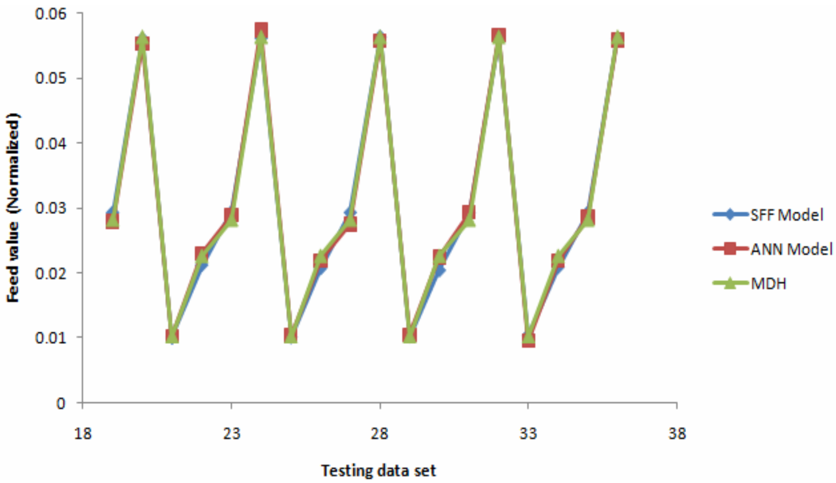


Fig. 21. Comparison of feed values between SFF, ANN and MDH

5. Conclusion

In this study, a fuzzy logic using expert rules and ANN model are used to predict machining parameters.

The fuzzy inference engine used in the model has successfully formulated the input-output mapping enabling an easy and effective approach for selecting optimal machining parameters. ANN was also found to be accurate in predicting the optimal parameters.

Both approaches can be easily expanded to handle more tool-workpiece materials combinations and it is not limited to turning process only and can be used for other machining processes like: milling, drilling, grinding, etc.

However the SFF is more user-friendly and compatible with the automation concept of a flexible and computer integrated manufacturing systems. It allows the operator, even unskilled to find the optimal machining parameters for an efficient machining process that can lead to an improvement of product quality, increase production rates and thus reducing product cost and total manufacturing costs.

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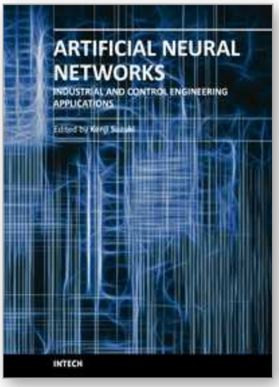

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Artificial neural networks may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications. The purpose of this book is to provide recent advances of artificial neural networks in industrial and control engineering applications. The book begins with a review of applications of artificial neural networks in textile industries. Particular applications in textile industries follow. Parts continue with applications in materials science and industry such as material identification, and estimation of material property and state, food industry such as meat, electric and power industry such as batteries and power systems, mechanical engineering such as engines and machines, and control and robotic engineering such as system control and identification, fault diagnosis systems, and robot manipulation. Thus, this book will be a fundamental source of recent advances and applications of artificial neural networks in industrial and control engineering areas. The target audience includes professors and students in engineering schools, and researchers and engineers in industries.