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ORIGINAL ARTICLE

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An economic and reliable tool life estimation procedure for turning

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Abstract The conventional methods of tool life estimation take a long time and consume a lot of work piece material. In this paper, a quicker method for the estimation of tool life is proposed, which requires less consumption of work piece material and tools. In this method the tool life is estimated by fitting a best-fit line on the data falling in the steady wear zone and finding the time till tool failure by extrapolation. Neural networks are used to predict lower, upper and most likely estimates of the tool life. Comparison between neural networks and multiple regression shows the superiority of the former. The paper also proposes a methodology for continuous monitoring of tool use in the shop floor and updating/obtaining the tool life estimates based on the shop floor feed back.

Keywords Dry turning · Multiple regression · Neural networks · Optimization · Tool life

1 Introduction

Starting from the work of Gilbert [1], optimization of the turning process has attracted the attention of a number of researchers. Most of the research works concentrate on finding a suitable optimization technique and testing the performance of proposed techniques by means of hypothetical examples [2–12]. In all the papers cited here, authors have assumed the existence of a reliable tool life equation, with known values of exponents. None of the authors have validated their technique by real life data in a shop floor environment. This is in spite of the known fact that the availability of a reliable tool life equation is crucial, but perhaps, the most difficult requirement for a reliable estimation of optimum cutting parameters. In comparison to the literature available on the optimization of the turning process, there are fewer publications on tool life estimation, some of the representative papers being [13–19].

Many times, in shop floors the tools are used in a very inefficient manner due to lack of proper information about tool life. A recent CIRP working paper [20] reports the survey result of a major cutting tool manufacturer as " ... In USA, the correct cutting tool is selected 50% of the time, the tool is used at the rated cutting speed only 58% of the time and only 38% of the tools are used up to their full tool life capability ... ." This indicates that most of the research works on the optimization of turning process could not cross the boundaries of academic research. Non-availability of reliable data on tool life for various tool-work material combinations is one of the major causes for this. Tool life testing requires a considerable number of tests, if reliable results are to be obtained. This implies a high consumption of time, work-material and cutting tools and is, therefore, a relatively expensive procedure. Constructing tool life curves at two different cutting speeds using ISO turning test, for example, often requires roughly forty hours of machining time [21]. Hegginbotham and Pandey [22] proposed a "variable rate turning" method in which 20 kg of material was consumed to estimate the dependency of tool life on cutting speed only.

In view of these, the objective of the present work is to develop a quicker method for the estimation of tool life. For tool life prediction purpose, use is made of neural networks, which have been used earlier also for the tool life estimation [16, 17]. However, the present work uses them more efficiently and provides the information regarding low, most-likely and high estimates of the tool life. Observing that Taylor's extended tool life equation does not fit over the whole domain, the present work suggests to fit different equations over different sub-domains. Multiple-regression technique is used for finding the exponents of tool life equations. The paper also suggests a methodology for continuous monitoring of tool use in the shop floor and updating/obtaining the tool life estimates based on shop floor feedback.

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2 Tool life estimation procedure

Tool life estimation involves a number of tests to be carried out at various cutting conditions till the failure of the cutting tool. This procedure not only consumes a number of tools, but also requires a lot of time and work material, especially while machining at the process conditions providing more tool life. In this work, a methodology is adopted, in which machining is carried out for 5–7 passes at each cutting condition. The wear after each cutting pass is noted and the time for a limiting flank wear is estimated by extrapolating the wear-time curve. The wear-time curve for most cutting tools follows a pattern similar to that shown in Fig. 1, having three distinct wear zones: initial wear, steady wear, and severe wear. A tool should be discarded before reaching the severe wear zone. A few tests carried out to test the behavior of TiN coated carbide tool while machining mild steel clearly showed a rapid increase in wear in the initial wear zone and an almost linear wear in the steady wear zone. Figure 2a, for example, shows the initial wear zone followed by the steady wear zone, whereas, in Fig. 2b, only a linear steady wear zone is depicted. In this case no data point fell in the initial wear zone, as the zone is of very small size.

Tool life is estimated by fitting a best-fit line on the data falling in the steady wear zone, and then finding the time by which a maximum flank wear of 0.8 mm would occur. The criterion of a maximum flank wear of 0.8 mm is based on literature, as well as, the experience of authors. Estimates can easily be modified for any other limiting value of the maximum flank wear.

Mathematically, if the best-fit equation is

$$w = a + bt \,, \tag{1}$$

where w is the flank wear, t is the time and a and b are constants, then the tool life T is given by

$$T = \frac{w_{\max} - a}{b} \,, \tag{2}$$

where $w_{\max}$ is the maximum flank wear. Once the tool life data for various cutting conditions are obtained, the tool life equation can be developed by means of neural network/regression. The following subsections describe the experiments and neural network/regression procedure.

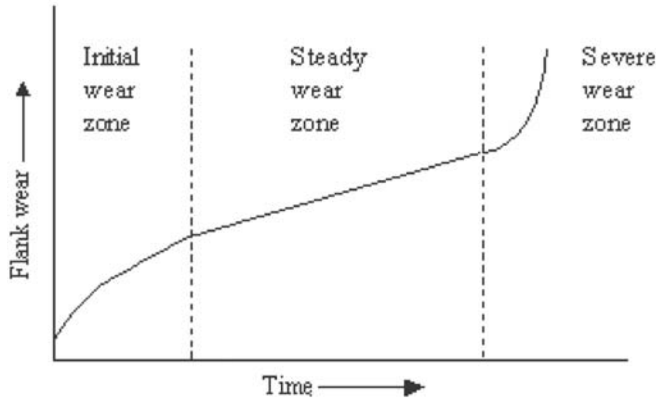


Fig. 1. Flank wear versus time curve for a typical tool

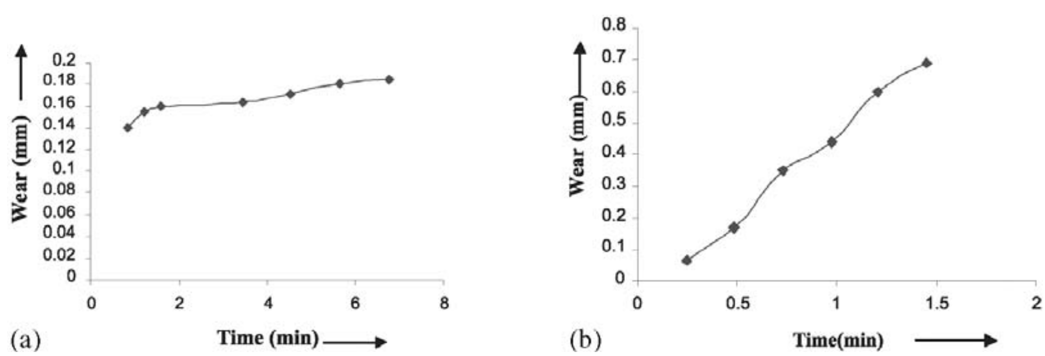
2.1 Experimental setup

For carrying out experiments, a HMT make NH-26 lathe was used. A 3-phase 11 kW induction motor, providing 23 speeds between 40 and 2040 RPM drives the spindle. The work piece used for the experiments was cut from rolled steel bars containing about 0.35% carbon. The hardness of steel was 130 BHN, yield strength 290 MPa and ultimate strength 477 MPa. Dry turning tests were conducted for predicting the tool life on a work piece of diameter ranging from 30 to 50 mm and lengths ranging from 110 to 130 mm. The ranges of process parameters were cutting speed 135–270 m/min, feed 0.04–0.32 mm/rev and depth of cut 0.3–1.2 mm. The cutting tools used were TiN coated tungsten carbide triangular inserts, TNMM 160404 type, Widia make. The ASA Tool signature was (−5°)-(−5.5°)-6°-6°-28°-0°-0.8 mm. For different cutting conditions machining was done for 5–7 passes and after each pass the maximum flank wear was recorded using an Axiotech microscope (Zeiss).

2.2 Design of experiments and neural network modeling

It was decided beforehand to use neural networks for the tool life estimation. The methodology used by Kohli and Dixit [23] for surface roughness prediction was used here, which is described very briefly in the context of the present problem. Here, a feed

Fig. 2a,b. Flank wear versus time curve for dry turning **a** cutting speed, $v = 135$ m/min, feed, $f = 0.32$ mm/rev, depth of cut, $d = 0.3$ mm **b** $v = 270$ m/min, $f = 0.32$ mm/rev, $d = 1.2$ mm



forward network consisting of one input layer of 3-inputs (cutting speed (v), feed (f) and depth of cut (d)) neurons, one hidden layer and one output layer of one neuron representing the tool life (T) was employed. Input and output parameters were put in natural logarithmic form and normalized to lie between 0.1–0.9.

First, eight experiments were carried out according to a 2^3 full factorial design, two levels for each input parameters being the minimum and maximum values in the corresponding ranges. Based on this, the effect of a factor can be calculated as [24]

$$\text{Effect of a factor} = \frac{\sum \text{responses at high levels} - \sum \text{responses at low levels}}{\text{half the number of runs in the experiment}} . \quad (3)$$

In the present work, effects of cutting speed, feed, and depth of cut were found to be -0.66, -1.17 and -0.51, respectively. Note that the effect is dependent on the ranges chosen for the parameter. For example, here, the ratio between maximum and minimum speed is 2, whereas it is 8 for feed. Hence, the magnitude of the effect of feed is more than that of speed. If both, speed and feed, had the same ratio between their maximum and minimum values, the effect of speed would have been more than the effect of feed.

The levels of a factor are increased in proportion to its effect. The parameter having the minimum effect (depth of cut in this case) is retained at two levels only, i.e. maximum and minimum values in the range. The number of levels for speed and feed were obtained as 3 and 5, respectively. Thus for speed, one value in the middle of the range is chosen and the other process parameters corresponding to this speed are taken at random. Similarly, in the case of feed, three additional levels are chosen to have a total of five equally spaced levels in the range. Thus, an initial training dataset of 2^3 is increased to 12. The size of the initial testing data set is kept as 8, as in [23]. A bigger data set size will provide more reliability in prediction. By optimizing for the number of neurons, learning rate and initial weights, the best network is fitted.

If the maximum percentage error in a testing data is more than 50%, the data is transferred to the training data set and one fresh data is added in the testing data set in lieu of it. It would have been better to add two data in the testing set in exchange for the one data transferred, as done in [23]. However, time and cost requirements in this work prohibited the authors to do that. This procedure is repeated till all data in the testing set provide an error of less than 50%. Based on a few replicates, it was concluded that a prediction accuracy of less than 50% is not achievable. In case the testing error in a data comes out to be more than twice the rms error, two replicates are generated to assess the correct tool life for that data.

2.3 Lower and upper estimates of tool life

For predicting the lower and upper estimate of the tool life, a simple modification of back-propagation algorithm, as proposed by Ishbuchi and Tanaka [25], is used. In the back-propagation algorithm, the error is propagated backwards such that it adjusts the weights of the network. In the case of prediction of upper estimate, the prediction should be a value greater than the experimental value. Hence, if the predicted value is slightly greater than the experimental value, a reduced value of the error is propagated backwards for modifying the weights. On the contrary, if the predicted value is less than the experimental value, complete error is propagated backwards. This is to ensure that the prediction is more than the experimental value. Thus, the error function is given by the following equation:

$$e_p = \begin{cases} \left(d_p - o_p\right)^2 \big/ 2 & d_p \geqslant o_p \\ w(u)\left(d_p - o_p\right)^2 \big/ 2 & d_p < o_p \end{cases} . \quad (4)$$

Here u, d_p, o_p denote the epoch number of the learning algorithm, experimental value and network output for a particular pattern (p), respectively. Factor, $w(u)$ is a monotonically decreasing function such that, $0 < w(u) \leqslant 1$ and $w(u) \to 0$ as $u \to \infty$. The decreasing function used here is

$$w(u) = \frac{1}{1 + (u/500)^3} . \quad (5)$$

In a similar way, a lower estimate of the data can be found out. In this case, the error function is given by:

$$e_p = \begin{cases} \left(d_p - o_p\right)^2 \big/ 2 & d_p < o_p \\ w(u)\left(d_p - o_p\right)^2 \big/ 2 & d_p \geqslant o_p \end{cases} . \quad (6)$$

2.4 Finding the exponents of Taylor's extended tool life equation

In most of the optimization algorithms (for example, in all papers cited here), an extended Taylor's tool life equation of the following form is required:

$$VT^n f^x d^y = C , \quad (7)$$

where the constants n, x, y and C are to be determined empirically. Fitting an equation to obtain these coefficients over a wide range yields a poor value of the coefficient of determination (R^2), which should be close to one. The coefficient of determination is used as a measure of how well the fit is, and is defined as

$$R^2 = 1 - \frac{\sum \left(y - \hat{y}\right)^2}{\sum \left(\bar{y} - y\right)^2} , \quad (8)$$

where $\hat{y}$ is the predicted value of the actual dependent variable y and $\bar{y}$ is the mean.

In the present work, parameter ranges were divided into three sub-ranges. Thus for each 27 zones, 27 different equations can be fitted by the multiple regression procedure. Data for the multiple regressions is obtained by the fitted neural network. In the optimization algorithm, the provision can be made to obtain the coefficients in the search space only, avoiding unnecessary computations. After the optimization algorithm determines the optimum values of speed, feed and depth of cut, a more refined tool life equation near to the optimum values can be obtained by conducting a number of experiments around the optimum.

3 Results and discussion of tool life prediction

Following the systematic procedure outlined in Sect. 2.2, neural networks were fitted for tool life prediction. The networks required a total of 22 data consisting of 14 training data and eight testing data. For assessing the performance of fitted networks, the following error measures were used:

$$\text{Absolute error in prediction for } i\text{th data} = (T_i - \hat{T}_i) \tag{9}$$

Percentage fractional error in prediction for ith data

$$= \frac{(T_i - \hat{T}_i)}{T_i} \times 100 \tag{10}$$

$$\text{Root mean square error, } (RMS_{err}) = \sqrt{\frac{\sum_{i=1}^{n} (T_i - \hat{T}_i)^2}{n}} \tag{11}$$

$$\text{Root mean square fractional error, } (RMS^f_{err}) = \sqrt{\frac{\sum_{i=1}^{n} \left(1 - \frac{\hat{T}_i}{T_i}\right)^2}{n}}, \tag{12}$$

where T_i is the estimated tool life, based on experiments and using Eq. 2, $\hat{T}_i$ is the predicted tool life and n is the number of data.

Tables 1 and 2 show the training and testing data, respectively. Table 3 shows the performance of the network. The root mean square fractional error is 29.1% for testing data. The maximum percentage fractional error of 48.6% is found in the sixth data, which has the lowest tool life among all testing data. The maximum absolute error in the testing data is 76.1 min for data number 4, where the actual tool life is 181.3 min. The percentage error in this case is 42%. In view of a number of random factors, these errors are reasonable.

In order to make a comparison with the multiple regression analysis, all 22 data were used for fitting the regression equation. Comparison between the multiple regression and neural network prediction has been carried out on the basis of various error measures and R^2 given by Eq. 8. Table 4 shows the comparison. It is seen that the coefficient of determination is very poor in the case of multiple regression. Hence, a satisfactory extended Taylor's tool life equation cannot be fitted over the whole domain. Various error measures provide a high value in the case of multiple regression as compared to neural network. Hence, neural networks provide much better estimates of tool life.

Figures 3a and 3b visually depict the lower, upper, most likely estimates and experimental values of tool lives for 14 training and eight testing data, respectively. The upper and lower

Table 1. Training data set

S. no.	v (m/min)	f (mm/rev)	d (mm)	T (min)
1	135	0.04	0.30	164.5
2	270	0.04	0.30	68.3
3	135	0.04	1.20	116.8
4	270	0.04	1.20	64.0
5	270	0.32	1.20	1.3
6	270	0.32	0.30	3.1
7	135	0.32	0.30	112.1
8	135	0.32	1.20	3.7
9	205	0.12	0.50	94.8
10	260	0.10	0.68	37.3
11	200	0.20	0.34	65.0
12	210	0.24	0.36	112.6
13	160	0.28	1.14	52.9
14	164	0.16	1.00	35.1

Table 2. Testing data set

S. no.	v (m/min)	f (mm/rev)	d (mm)	T (min)
1	212	0.14	0.80	44.9
2	180	0.08	1.10	57.9
3	140	0.06	0.70	88.7
4	175	0.05	0.60	181.3
5	220	0.07	0.38	90.9
6	210	0.20	0.80	37.0
7	195	0.08	0.62	71.0
8	150	0.10	0.50	189.0

Table 3. Errors in training, testing and total data

Error measure	Error values Training data	Testing data	Total data
RMS_{err} (min)	14.4	37.3	25.2
RMS^f_{err} (%)	21.0	29.1	24.6
Maximum absolute error (min)	31.7	76.1	76.1
Maximum fractional error (%)	32.1	48.6	48.6

Table 4. Comparison of neural networks and multiple regression

Performance Measures	Neural networks values	Multiple regression values
R^2	0.92	0.34
RMS^f_{err} (%)	24.6	166.9
RMS_{err} (min)	25.2	74.0
Maximum absolute error (min)	76.1	292.0
Maximum fractional error (%)	48.6	536.1

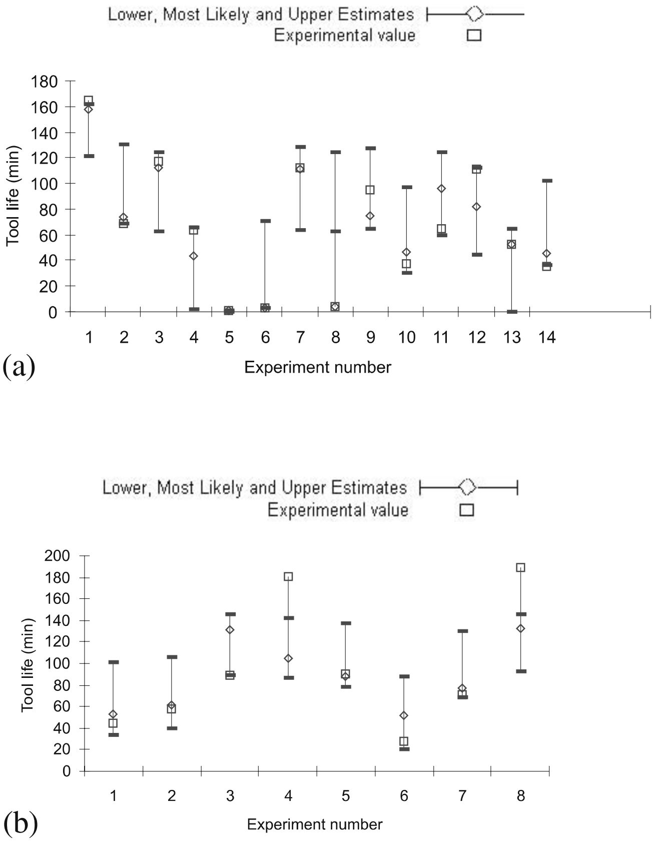


Fig. 3a,b. Predicted values versus experimental value of tool lives in dry turning by carbide tool **a** for training data **b** for testing data

estimates were obtained by following the procedure described in Sect. 2.3. The network was trained up to the error goal, which provided all the experimental data falling between the upper and lower estimates. In testing data, the experimental values of tool lives lie between the predicted lower and upper estimates, except in two cases. The somewhat large difference in the two estimates is due to randomness of the turning process. It is seen that in 17 cases the error in prediction is less than 40%. Only in five cases error is more than 40% with the maximum of 48.6%.

In order to assess the possibility of fitting an extended Taylor's tool life equation, the procedure outlined in Sect. 2.4 was adopted. Twenty-two data were generated artificially (using the fitted neural network) in a sub domain of $v = 160–220$ m/min, $f = 0.14–0.22$ mm/rev and $d = 0.3–0.6$ mm to fit the extended Taylor's tool life equation. Then the equation was fitted using multiple regressions. Values of R^2, RMS^f_{err} and RMS_{err} for these data were obtained as 0.98, 1.71% and 1.86 min, respectively. Exponents of the equation were obtained as $n = 0.54$, $x = 0.08$, $y = 0.34$ and $C = 1381$.

In the estimation of the tool life using the method proposed in this paper, effectively four tools were consumed. The total work piece material consumed was 9.5 kg. This quantity is much less than the 20 kg consumed by the method proposed by Heggin-botham and Pandey [22] and other conventional methods for tool life estimation.

4 Updating/obtaining Taylor's tool life exponents based on shop floor feedback

Tool life estimation is carried out by means of limited data and using some failure criterion such as the maximum flank wear of 0.8 mm. It is essential to obtain the feedback from the shop floor about tool usage. This will help in monitoring the efficient utilization of tools as well as updating the estimates, if necessary. With modern CNC machines, it is possible to keep complete machining history of the tool. This information can be communicated via intranet/internet.

Let a tool operate at n different machining conditions before failure, time of machining at the ith cutting condition being t_i. If T_i^l, T_i^u and T_i^m are the lower, upper and most likely estimates of the tool life, then the following relations should hold good:

$$\sum_{i=1}^{n} \frac{t_i}{T_i^l} \geqslant 1 \tag{13}$$

$$\sum_{i=1}^{n} \frac{t_i}{T_i^u} \leqslant 1 \tag{14}$$

$$1 - \varepsilon \leqslant \sum_{i=1}^{n} \frac{t_i}{T_i^m} \leqslant 1 + \varepsilon\,, \tag{15}$$

where ε is a small number close to zero, depending on the randomness in the tool lives and accuracy of prediction.

Non-satisfaction of inequality Eq. 13 means the underutilization of tools. Similarly, non-satisfaction of inequality Eq. 14 implies over utilization of the tool. For a particular tool j, error in prediction of the most likely estimate can be defined as

$$e_j = \sum_{i=1}^{n} \frac{t_i}{T_i^j} - 1\,. \tag{16}$$

If for all the tools, the error is of the same sign, then either the tool use in the shop floor should be monitored or the tool life estimate should be revised. If the errors in prediction are large but more or less equally distributed around zero, it indicates a large variation in the quality of tools.

Tool life exponents can be modified after a sufficient number of data is available. If the history of m number of tools is available, tool life exponents can be obtained by minimizing the following objective function:

$$f = \sum_{j=1}^{m} \left(\sum_{i=1}^{n} \frac{t_i^j}{T_i^j} - 1 \right)^2 , \tag{17}$$

where for the jth tool, operating at ith cutting condition,

$$T_i^j = \frac{C^{1/n}}{(f_i^j)^{x/n} (d_i^j)^{y/n} (v_i^j)^{1/n}}\,. \tag{18}$$

In the objective function apart from the shop floor data, initial test data may also be included. The above optimization problem is solved using the Simplex search method [26]. The initial guess for C, n, x, y is taken from test data.

The entire methodology works as follows:

1. Collect data from the shop floor. Study the cases violating the inequalities Eq. 13 and Eq. 14. If the discrepancy is due to the operator's wrong strategies of tool change, he should be asked to change the strategy. However, if the operator's strategy is sound, the tool estimates should be modified by changing the failure criterion and/or by carrying out a few sets of experiments.
2. In case inequalities Eq. 13 and Eq. 14 are satisfied, but the values of errors given by Eq. 16 are high, and in same direction, tool use in the shop floor should be examined and reviewed. If the errors are large and more or less equally distributed around zero, the vendor development department should be informed about the large variation in tool estimation.
3. If the shop floor practice is all right and data from the shop floor is reliable, the coefficients are updated using the Simplex search method.

An example:
For demonstrating the feasibility of obtaining tool-life exponents using the Simplex search method, an example is taken. Let us assume that data for eight different tools has been collected from internet/intranet. In this example, hypothetical data is generated using the tool life equation:

$$VT^{0.2}f^{0.15}d^{0.2} = 273\,. \tag{19}$$

Data should be from a narrow domain of cutting parameters and should cover a number of cutting conditions. The data for tools (Table 5) was used for minimization of the objective function Eq. 17. The optimization routine provides exponents as $x = 0.15$, $y = 0.15$, $n = 0.2$ and $C = 273$. These values were the same as the exponents used for generating the data. The solution process took about 3 min on a Pentium III machine.

Table 5. Hypothetical data of eight tools used in the shop floor

Tool no.	v (m/min)	f (mm/rev)	d (mm)	Turing time (min)
1	180	0.14	0.6	40.00
	225	0.14	0.9	4.02
2	190	0.20	0.6	18.00
	200	0.16	0.9	9.83
3	185	0.20	0.7	17.00
	195	0.14	0.8	14.43
4	210	0.16	0.6	15.00
	220	0.14	0.9	5.52
5	200	0.16	0.6	19.00
	180	0.20	0.7	14.99
6	190	0.14	0.7	24.00
	185	0.16	0.8	12.86
7	210	0.20	0.7	9.00
	220	0.16	0.6	5.77
8	225	0.20	0.6	11.00
	195	0.14	0.9	6.50

5 Conclusion

In the present work, a procedure to estimate tool life in an economical and reliable manner has been developed. Utilizing the property of linear tool wear and time relation in a steady wear zone, time until failure was estimated by partially wearing the tools. Neural networks were used to find lower, upper and most likely estimates of tool life. It is observed that in most of the cases, the experimental value is close to the predicted most likely estimate and within the upper and lower estimates. In a few cases, the predicted values differ considerably from experimental values. This is because of the presence of many random factors. However, it is seen that neural networks provide much better estimates of tool life as compared to multiple regression. The procedure required less consumption of tool and workpiece material.

A methodology has been proposed for monitoring the tool usage based on the shopfloor feedback, which can be obtained using internet/intranet in an efficient manner. If the large number of reliable shop floor data is available, tool life exponents can be estimated in an inverse manner without conducting tests. This is demonstrated by taking an example. Future work will include implementing the above strategy in a real factory making use of the internet.

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