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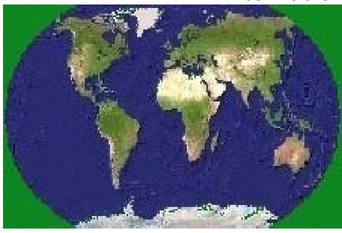

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Development of artificial neural network model to correlate the cutting and process parameters in high speed machining (HSM)

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Abstract
The three major manufacturing sectors where High Speed Machining is widely applied are: Aerospace, Die and Mold manufacturing and automotive sectors. The High Speed Machining implies both high velocity machining involving high spindle speeds and at high feed rates with significantly increased spindle speeds. High Speed Machining in fact reduces total machining time as well as reduces bench time. Though high speed machining facilitates faster material removal rates, the process can be made efficient only if optimal combination of machining parameters is selected and tool path is to be optimized.
Much research and development work has been carried out in the area of High speed machining of aluminum alloys, titanium alloys, steels and Super alloys. A major factor in the adoption of high speed machining has been the desire to improve tolerances in cutting operations. With high speed machining, most of the heat generated in cutting is removed by the chip, so the tool and the work piece remains close to ambient temperature Apart from that high speed machining leads to reduction in cutting forces that means low power consumption.
The study is concerned with the effect of various parameters (cutting speed, feed, depth of cut etc.) on tool life, surface roughness and cutting temperature during HSM process. The data of different experiment are collected and then they are represented in the suitable Taguchi's table for three different work piece and tool combination (AISI-4140 Steel & Al203 + TiCN Mixed Ceramic, AISI-1117 Steel & Cemented Carbide, Inconel 718 & Al203 + TiCN Mixed Ceramic). After obtaining the data in organized form an ANN (artificial neural network) model was developed to have a clear representation of the data collected.
The ANN model will give the user an Optimized value of surface roughness, flank wear and cutting temperature for the given input parameters. As neural network has to train with an optimized amount of data, an L 27 array is used. With the given data the neural network is trained and then the validation of the model is performed i.e. for a given set of input parameters we obtained the value of output and this value is compared with the actual output to ensure the validity of the ANN model. The result from the validation show that the error fell within the range of 0% to 3%. Hence it shows that the artificial neural network model is efficient to correlate the cutting and process parameters and can be integrated into an intelligent manufacturing system for solving complex machining optimization problems.

Keywords: Development; Artificial Neural Network Model; Cutting and Process Parameters; High Speed Machining.

1. Introduction
1.1 Manufacturing
The word manufacturing is derived from the Latin word *manu factus* meaning made by Hand. Manufacturing in the broadest sense is the process of converting raw material into product. A manufactured product has to undergo many processes which adds its monetary value.
Thus manufacturing is a value adding process. It encompasses:
1. Design of product
2. The selection of raw product
3. The sequence through which the products are manufactured

The field of manufacturing engineering and technology continues to advance rapidly. Transcending disciplines and driving economic growth. This challenging and broad topic has continued to incorporate new concepts at an increasing rate making manufacturing a dynamic and exciting field of study.

1.2 Machining
Machining is a process of material removal from the raw material to the final product.

A variety of shapes can be produced by machining.
The machine where material removal operation is performed is called machine tool. Their construction and characteristics greatly influence these operations, as well as product quality, surface finish and dimensional accuracy. It is important to view machining and manufacturing operation as a system consisting of the work piece, cutting tool and machine. Material removal process is necessary in manufacturing operation for following reasons:
1. Closer dimensional accuracy
2. Producing internal shapes and sharp geometrical features
3. for finishing operation
4. Economical considerations

1.3 Lathe Machine

A lathe is generic description for a rigid machine tool designed to remove material from a work piece, through the action of the cutting tool. They are originally designed to machine metals; however, with the advent of plastics and wide range of applications, and a broad range of materials. The machine has been greatly modified for various applications; however a familiarity with the basics shows the similarities between types. These machines consist of, at the least, a headstock, bed, carriage and tailstock.

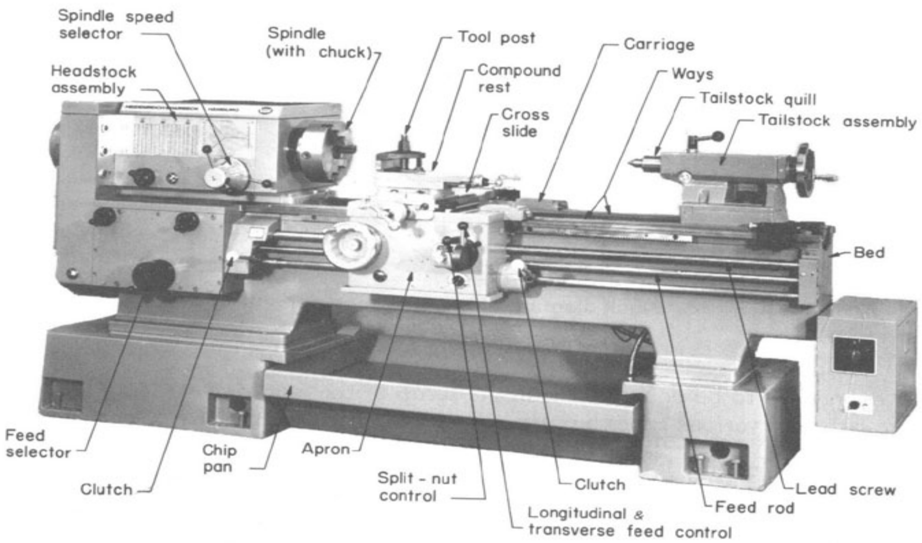

Fig 1: Lathe Machine

2. Taguchi Experimental Design

Every experimenter has to plan and conduct experiments to obtain enough and relevant data so that he can infer the science behind the observed phenomenon. He can do so by:

(1) Trial-and-error approach

Performing a series of experiments each of which gives some understanding. This requires making measurements after every experiment so that analysis of observed data will allow him to decide what to do next – "Which parameters should be varied and by how much". Many a times such series does not progress much as negative results may discourage or will not allow a selection of parameters which ought to be changed in the next experiment. Therefore, such experimentation usually ends well before the number of experiments reaches a double digit! The data is insufficient to draw any significant conclusions and the main problem (of understanding the science) still remains unsolved.

(2) Design of experiments

A well planned set of experiments, in which all parameters of interest are varied over a specified range, is a much better approach to obtain systematic data. Mathematically speaking, such a complete set of experiments ought to give desired results. Usually the number of experiments and resources (materials and time) required are prohibitively large. Often the experimenter decides to perform a subset of the complete set of experiments to save on time and money! However, it does not easily lend itself to understanding of science behind the phenomenon. The analysis is not very easy (though it may be easy for the mathematician / statistician) and thus effects of various parameters on the observed data are not readily apparent. In many cases, particularly those in which some optimization is required, the method does not point to the BEST settings of parameters. A classic example illustrating the drawback of design of experiments is found in the planning of a world cup event, say football. While all matches are well arranged with respect to the different teams and different venues on different dates and yet the planning does not care about the result of any match (win or lose)!!!! Obviously, such a strategy is not desirable for conducting scientific experiments (except for coordinating various institutions, committees, people, equipment, materials etc.).

(3) Taguchi Method

Dr. Taguchi of Nippon Telephones and Telegraph Company, Japan has developed a method based on “ORTHOGONAL ARRAY” experiments which gives much reduced “variance” for the experiment with “optimum settings “of control parameters. Thus the marriage of Design of Experiments with optimization of control parameters to obtain BEST results is achieved in the Taguchi Method. "Orthogonal Arrays" (OA) provide a set of well balanced (minimum) experiments and Dr. Taguchi's Signal-to-Noise ratios (S/N), which are log functions of desired output, serve as objective functions for optimization, help in data analysis and prediction of optimum results.

2.1 Steps in taguchi methodology

Taguchi method is a scientifically disciplined mechanism for evaluating and implementing improvements in products, processes, materials, equipment, and facilities. These improvements are aimed at improving the desired characteristics and simultaneously reducing the number of defects by studying the key variables controlling the process and optimizing the procedures or design to yield the best results. The method is applicable over a wide range of engineering fields that include processes that manufacture raw materials, sub systems, products for professional and consumer markets. In fact, the method can be applied to any process be it engineering fabrication, computer-aided-design, banking and service sectors etc. Taguchi method is useful for 'tuning' a given process for 'best' results. Taguchi proposed a standard 8-step procedure for applying his method for optimizing any process,

2.3 Steps in taguchi methodology

Step-1: Identify the main function, side effects, and failure mode
Step-2: Identify the noise factors, testing conditions, and quality characteristics
Step-3: Identify the objective function to be optimized
Step-4: Identify the control factors and their levels
Step-5: Select the orthogonal array matrix experiment
Step-6: Conduct the matrix experiment
Step-7: Analyze the data, predict the optimum levels and performance
Step-8: Perform the verification experiment and plan the future action

2.4 Types of Orthogonal Arrays (Taguchi Designs)

L4: Three two-level factors
L8: Seven two-level factors
L9: Four three-level factors
L12: Eleven two-level factors
L16: Fifteen two-level factors
L16b: Five four-level factors
L18: One two-level and seven three-level factors
L25: Six five-level factors
L27: Thirteen three-level factors
L32: Thirty-two two-level factors
L32b: One two-level factor and nine four-level factors
L36: Eleven two-level factors and twelve three-level factors
L50: One two-level factors and eleven five-level factors
L54: One two-level factor and twenty-five three-level factors
L64: Thirty-one two-level factors
L64b: Twenty-one four-level factors
L81: Forty three-level factors

3. Artificial Neural Network Modelling

Three different work material and cutting tool combinations is being considered in this work, viz.
1. WORK MATERIAL - AISI-4140 STEEL
CUTTING TOOL - Al2O3 + TiCN MIXED CERAMIC
2. WORK MATERIAL - AISI-1117 STEEL
CUTTING TOOL - CEMENTED CARBIDE
3. WORK MATERIAL - INCONEL 718
CUTTING TOOL - Al2O3 + TiCN MIXED CERAMIC

For a given set of input parameters the value of output obtained is compared with the neural network value. The result show that the error fell within the range of 0% to 3%. Hence the artificial neural network model is efficient to correlate the cutting and process parameters and can be integrated into an intelligent manufacturing system for solving complex machining optimization problems. The following are the tables formulated to compare the actual and neural network values for the tool combinations taken.

4. Results and Discussion

4.1 Comparison Tables

Work material-AISI-4140 Steel, Cutting tool-Al 2O3+ TiCN Mixed Ceramic

S.NO	Vc (m/min)	d (mm)	f (mm/rev)	Actual Value			Neural Network Value			%Error		
				Ra (µm)	VB (mm)	Temp(^{0}C)	Ra	VB	Temp	Ra	VB	Temp
1	250	1.00	0.15	1.282	0.1313	764.4	1.273	0.13052	766.7	0.674	0.594	0.303
2	300	1.25	0.20	1.326	0.11365	901.7	1.332	0.11544	900.0	0.489	1.576	0.193
3	200	0.75	0.25	1.604	0.18225	634.0	1.601	0.18389	635.1	0.194	0.900	0.174
4	250	1.25	0.20	1.458	0.16865	818.2	1.482	0.16772	817.2	1.626	0.551	0.126
5	300	0.75	0.25	1.340	0.07225	801.0	1.343	0.07170	790.6	0.208	0.765	1.298
6	200	1.00	0.15	1.414	0.1863	680.9	1.408	0.18731	679.5	0.453	0.540	0.207

Work material-AISI 1117 Steel, Cutting tool- Cemented Carbide

S.NO	Vc (m/min)	d (mm)	f (mm/rev)	Actual Value			Neural Network Value			%Error		
				Ra (µm)	VB (mm)	Temp(^{0}C)	Ra	VB	Temp	Ra	VB	Temp
1	250	1.00	0.15	0.770	0.1563	230.1	0.770	0.1554	231.6	0.029	0.570	0.689
2	300	1.25	0.20	1.163	0.1262	289.2	1.135	0.1252	289.6	2.408	0.727	0.133
3	200	0.75	0.25	1.921	0.2348	210.4	1.897	0.2351	210.5	1.226	0.158	0.071
4	250	1.25	0.20	1.243	0.2012	260.7	1.241	0.2026	259.8	0.135	0.715	0.336
5	300	0.75	0.25	1.762	0.0848	267.4	1.760	0.0853	268.6	0.098	0.596	0.445
6	200	1.00	0.15	0.849	0.2313	201.6	0.844	0.2301	200.3	0.546	0.512	0.606

Work material-Inconel 718, Cutting Tool- Al 2O3+ TiCN Mixed Ceramic

S.NO	Vc (m/min)	d (mm)	f (mm/rev)	Actual Value			Neural Network Value			%Error		
				Ra (µm)	VB (mm)	Temp(^{0}C)	Ra	VB	Temp	Ra	VB	Temp
1	250	1.00	0.15	1.206	0.5372	898.0	1.208	0.5353	899.0	0.219	0.348	0.114
2	300	1.25	0.20	1.074	0.7354	965.8	1.082	0.7397	979.5	0.754	0.597	1.419
3	200	0.75	0.25	1.507	0.2908	894.7	1.497	0.2952	893.6	0.603	1.541	0.123
4	250	1.25	0.20	1.316	0.7139	969.5	1.299	0.7119	963.2	1.302	0.271	0.651
5	300	0.75	0.25	1.023	0.3338	887.3	1.033	0.3326	892.2	1.073	0.350	0.551
6	200	1.00	0.15	1.448	0.5157	901.7	1.435	0.5197	908.2	0.890	0.781	0.722

5. Validation

It would be unwise to design a network, train it and then into practice immediately. Its accuracy and capabilities should first be tested, evaluated and scrutinized. The testing process is known as validation. It can be said that the validation process can in some cases be more important than the training process, as small errors can be detected and fixed. If this is not done, small errors could result in misleading outputs from your network. The network will therefore be useless as its outputs will be unreliable and incorrect.

As with training, the programmer collects a set of examples from the external environment and the network with the validation set. It is important that the network is unfamiliar with the examples in the set as "the purpose of the validation set is to provide an unbiased indication of what can be expected of the network".

It is very important that the validation set is not used as part of the training set for the above reason. If the network is found to have performed poorly in the Validation set, there are several things that might have caused this. Firstly it may be found that the connection weights of the inputs are not sufficient, in which case these weights have to be adjusted accordingly. It may also be found that the training set was incomplete, in which case it is necessary to retrain the network using a different training set. If the training set is the problem, the best way to handle it is to combine the initial training set with the initial validation set to create one large training set. It is then necessary to collect new examples for a new validation set. It can therefore be said that the purpose of validation set is to test the network's capabilities before it is implemented for proper use.

5.1 Validation Process
Validation data were collected from various journals and research papers. However the data was not collected in a systematic way, rather, readings were taken at random intervals throughout the machining process. It was necessary to ensure that the values chosen for this purpose lied within the range covered by the model. This was because, even though the ANN model developed does predict values for data lying outside the range, at times the predictions tend to become erratic and inconsistent. It was also necessary to ensure that the no validation data matched with any of the training data. The same data were then fed into the ANN model, and its predictions were noted. The values for all the three work piece tool combination have been tabulated below. The actual values and the predicted values are tabulated for each of the combinations. The error percentages have also been tabulated for all the three work piece tool combination

6. Conclusion
Three different work material and cutting tool combination is being considered in this work, viz.

1. WORK MATERIAL - AISI-4140 STEEL
CUTTING TOOL - Al_2O_3 + TiCN MIXED CERAMIC
2. WORK MATERIAL - AISI-1117 STEEL
CUTTING TOOL - CEMENTED CARBIDE
3. WORK MATERIAL - INCONEL 718
CUTTING TOOL - Al_2O_3 + TiCN MIXED CERAMIC

Data was collected from various journals and research papers, after which it was tabulated. Finally with the help of large amount of data collected earlier, the orthogonal arrays were made. It was ensured that cutting conditions were same for each combination.

Finally an ANN model was developed from the data collected. The model correlates the cutting parameters (speed, depth of cut and feed) and the process parameters (surface roughness, flank wear and temperature). This model can be used to predict the values of process parameters for any given set of cutting parameters. The validation of the ANN model was done to ensure its reliability and accuracy. From the above graph and tabular columns the percentage error found between actual and predicted values lies within the range of 0% to 3%. The given artificial neural network model can be accepted as the errors are well within the satisfactory range. This amount of accurate predictions was achieved by optimization of neural network model for the given problem. The condition of optimization of neural network is:

The size of the neural network must be optimized i.e. the size of neural network must neither be too small nor too large. Too small neural network fail to converge for the answer of the problem, whereas larger network tend to memorize the output and the output is erratic for values other then the training data. The optimization of the neural network size was done by hit and trial method.

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