

Optimization of Spindle loading and Tool Wear for CNC Turning Machine by Using Intelligent System

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Abstract

Intelligent knowledge based system (IKBS) is developed for optimizing dry CNC turning process using Taguchi method, CNC Machine, EN19 steel as the work piece material, and Cutting Insert. Tool wear and spindle loading which are the machining parameters, spindle speed, feed rate, and depth of cut, are optimized through the intelligent knowledge based system (IKBS). The experimental CNC turning machine is used to evaluate IKBS. IKBS is developed to determine the effect of the machining parameters such as tool wear and spindle loading. The simultaneous optimization is done by IKBS. Four levels of each machining parameter are used in experimental verification on Model PTC 600, CNC lathe machine tool of PRAGA. The experimental verification designed based on Taguchi's method is used to evaluate the effect of the machining parameters on individual responses of IKBS. The simultaneous optimization is done by intelligent knowledge based system. The optimization of complicated multi-performance characteristics is simplified through this approach. Tool wear and spindle loading are two characteristics on the basis of which the machining parameters, spindle speed, feed rate, loading and depth of cut, are optimized through IKBS.

Keywords: Intelligent system, lathe Machine, Optimization, Spindle loading, Tool Wear.

1. Introduction

Turning is the most widely used among all the cutting processes. Turning is used to reduce the diameter of the workpiece, usually to a specified dimension, and to produce a smooth finish on the metal [1]. The increasing importance of turning operations is gaining new dimensions in the present industrial age, in which the growing competition calls for all the efforts to be directed towards the economical manufacture of machined parts [2]. The optimization of machining parameters increases the utility for machining economics and the product quality increases to a great extent as well [3]. The machining process on a CNC lathe is programmed by speed, feed rate and cutting depth, which are frequently determined based on the job shop experiences. However, the machine performance and the product characteristics are not guaranteed to be acceptable. Therefore, the optimum turning conditions have to be accomplished [4]. Taguchi techniques have been used in this study which is used by lot of researchers for optimizing surface roughness [2], tool wear [5], tool life [6], power consumption [1], and cutting temperature [7] etc. Many of the economic and technical problems of the machining are caused directly or indirectly by the heating action caused due to cutting action. Excessive temperatures directly influence the temperatures of

importance to tool wear on the tool face and tool flank and inducing thermal damage to the machined surface [8] [9]. All these difficulties lead to high tool wear, low material removal rate (MRR) and poor surface finish [5, 10, 11]. The objective of this work is to obtain optimal settings of turning process parameters namely spindle speed, feed rate and depth of cut on the basis of multi-performance characteristic, to yield optimal machining (turning) parameters while machining EN19 steel with carbide tools in a CNC machine tool environment. The response parameters to be measured are tool wear and spindle loading. IKBS is used to accomplish this objective. The traditional design of product, the preceding constraints and limitations are considered sequentially. In order to reduce the product development cycle time and cost and increase quality and productivity, concurrent (simultaneous) design of product and process has been introduced. The basic idea of concurrent engineering (CE) is to shorten the time horizon in which the design and manufacturing constraints are introduced. CE refers to integration of product design and manufacturing processes. It integrates various activities within the broad scope of the product life cycle [12-15]. In CE, the product design is viewed as a strategic task that has a major effect on the manufacturing activities. Design of product determines their quality and 70 to 80 % of the final production cost [16] and 70 % of the life cycle cost of a product are determined at the conceptual design stage [17]. Product design in CE is viewed as a teamwork approach [18]. Consequently, integration requires that quantitative relationships among customer requirement, marketing, product design, materials, manufacturing process and equipment capabilities, and relatives be well understood. In this way for example changes in material requirements, product types, or market demand can be accommodated. Also, high quality is far more attainable via the integration of design and manufacturing [19]. The goal of intelligent knowledge based system is the capability to conduct an intellectually demanding task in the way that a human expert would. The field of knowledge required to perform this task is called the domain of the artificial intelligent system. Expert system utilizes a knowledge base containing facts, data, definitions, and assumptions. They also have the capacity for heuristic approach that is making good judgment on the basis of discovery and revelation, and making high probability guesses just as a human expert would [20].

2. Intelligent Knowledge based system (IKBS)

The intelligent knowledge based systems is the computer applications developed to solve complex problems in a particular domain at the level of extra-ordinary human intelligence and expertise. The intelligent knowledge based systems (IKBS) are capable of advising, instructing and assisting human in decision making, demonstrating, deriving a solution, diagnosing, explaining, interpreting input, predicting results, justifying the conclusion and suggesting alternative options to a problem. The components of IKBS include knowledge base, interface engine and user interface. Knowledge base: It contains domain-specific and high-quality knowledge. Knowledge is required to exhibit intelligence. The success of any ES majorly depends upon the collection of highly accurate and precise knowledge. Knowledge is combination of data and information. The data is collection of facts. The information is organized as data and facts about the task domain. Data, information, and past experience combined together are termed as knowledge. The knowledge base of an intelligent system is a store of both, factual and heuristic knowledge. Factual Knowledge is the information widely accepted by the knowledge engineers and scholars in the task domain. Heuristic knowledge

is about practice, accurate judgment, one’s ability of evaluation, and guessing. Knowledge representation is the method used to organize and formalize the knowledge in the knowledge base. It is in the form of IF-THEN-ELSE rules. Knowledge acquisition in IKBS is very important, because success of any intelligent system depends on the quality, completeness, and accuracy of the information stored in the knowledge base. In this research, factual knowledge is that knowledge of design and manufacturing that is widely shared, typically found in textbooks or journals, and commonly agreed upon by those knowledgeable in the design and manufacturing field. Heuristic knowledge is the less rigorous, more experiential, more judgmental knowledge of performance. Both types of knowledge are used in this intelligent knowledge based system. It is the knowledge of good practice, good judgment in design and manufacturing. The knowledge base is formed by readings from various experts, scholars, and the knowledge engineers. The knowledge engineer is a person with the qualities of empathy, quick learning, and case analyzing skills. He acquires information from subject expert by recording, interviewing, and observing him at work, etc. He then categorizes and organizes the information in a meaningful way, in the form of IF-THEN-ELSE rules, to be used by inference machine. The knowledge engineer also monitors the development of the intelligent system. Components of any intelligent knowledge based system are demonstrated in Figure 1.

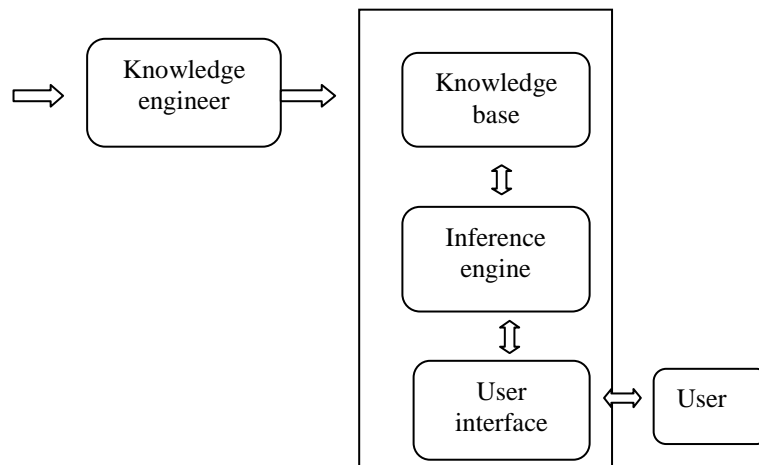


Figure1. Components of IKBS

Interface Engine: Use of efficient procedures and rules by the interface engine is essential in deducting a correct, flawless solution. In case of knowledge-based system, the interface engine acquires and manipulates the knowledge from the knowledge base to arrive at a particular solution. In case of rule based intelligent system, inference engine doing the following actions: 1-Applies rules repeatedly to the facts, which are obtained from earlier rule application. 2-Adds new knowledge into the knowledge base if required. 3- Resolves rules conflict when multiple rules are applicable to a particular case. To recommend a solution, the interface engine uses the following strategies 1- Forward chaining; 2- Backward Chaining. If the chaining starts from a set of conditions and moves toward some conclusion, the method is called forward chaining. Forward chaining strategy is a strategy to answer the question, “What can happen next?” Here, the interface engine follows the chain of conditions and derivations and finally deduces the outcome. It considers

all the facts and rules, and sorts them before concluding to a solution. This strategy is followed for working on conclusion, result, or effect, for example prediction of share market status as an effect of changes in interest rates. Backward chaining strategy: If the conclusion is known (for example, a goal to be achieved) but the path to that conclusion is not known, then reasoning backwards is called for, and the method is backward chaining. These problem-solving methods are built into program modules called inference engines or inference procedures that manipulate and use knowledge in the knowledge base to form a line of reasoning for design and manufacturing. The knowledge base which an expert uses is what he learned at school, from colleagues, and from years of experience. A typical backward chaining strategy is demonstrated in Figure 2.

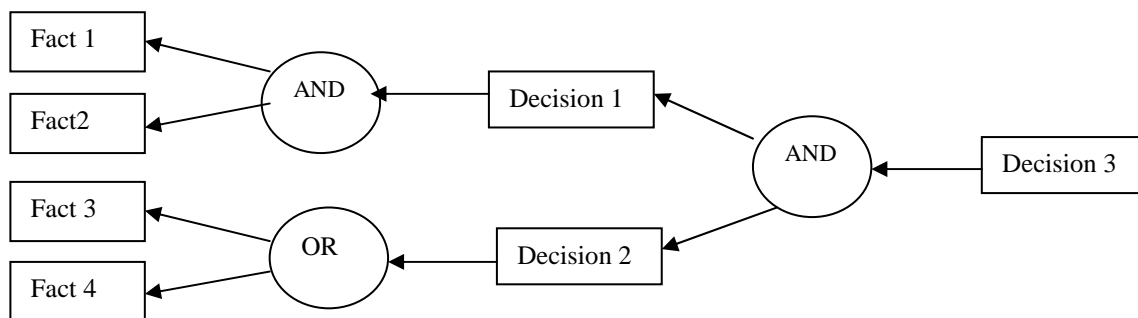


Figure 2. A Typical Backward Chaining Strategy

3. Design of Experiments

The experimental layout based on Taguchi’s Method is design.

3.1 Workpiece Material

EN19 steel is the work material selected to carry out the experiments. It offers good ductility and shock resisting properties combined with resistance to wear. It is a high tensile engineering steel with tensile strength of 850-1000 N/mm². EN19 steel is suitable for applications such as gears, bolts, studs and a wide variety of applications where a good quality high tensile steel grade is suited. Table 1 shows the chemical composition of EN19 steel. Work piece dimensions were Ø54 mm x 120 mm.

Table 1. Chemical Composition Of EN19 Steel

Carbon	Manganese	Chromium	Molybdenum	Silicon	Phosphorous	Sulphur
0.35-0.45%	0.50-0.80%	0.90-1.50%	0.20-0.40%	0.10-0.35%	0.035% max	0.050% Max

3.2 Cutting Inserts

In tests, coated carbide inserts of ISO designation TNMG 160404CQ with chip breaker geometry have been used for experimentation. The insert consists of 6 cutting edges. To study the effect of tool wear, each experiment is to be conducted using newer cutting edge. The cutting insert can be used within some ranges of cutting parameters only, which are as follows:

- Cutting velocity: (150-320) m/min

- Feed: (0.12-0.32) mm/rev
- Depth of cut: (0.50-3.00) mm

3.3 Machine Tool

Model PTC 600, CNC Lathe machine tool of PRAGA used in this experiment is demonstrated in Figure 3. In this research, coated carbide inserts of ISO designation TNMG 160404CQ with chip breaker geometry have been used for experimentation. To study the effect of tool wear, each experiment is to be conducted using newer cutting edge.



Figure3. Model PTC 600, CNC Lathe Machine Tool OfPRAGA

3.4. Measurement of Tool Wear and Spindle Loading

Tool flank wear of the worn out inserts are to be measured with the help of a “Measuring Projector MP-320” having magnification in the range of 10-100X. CNC Lathe Setup Spindle loading refers to the percentage of total load that is exerted on the spindle. Spindle loading refers to the percentage of total load that is exerted on the spindle. It is noted down directly from control panel of the CNC lathe.

3.5. Design of Experiments

The experimental layout is designed based on Taguchi’s L16 orthogonal array. Cutting parameters and levels used in experiment are given in Table 2.

Table 2. Cutting Parameters and Their Levels

Cutting parameter	Unit	Level 1	Level 2	Level 3	Level 4
Spindle speed	rpm	900	1000	1100	1200
Feed rate	mm/rev	0.14	0.17	0.20	0.23
Depth of cut	mm	0.5	0.75	1.00	1.25

In this research, coated carbide inserts of ISO designation TNMG 160404CQ with chip breaker geometry have been used for experimentation. To study the effect of tool wear, each experiment is to be conducted using newer cutting edge. The cutting insert can be used within some ranges of cutting parameters only, which are as follows:

- Cutting velocity: (150-320) m/min
- Feed: (0.12-0.32) mm/rev
- Depth of cut: (0.50-3.00) mm

Experimental results of tool wear and spindle loading are shown in Table 3.

Table 3. Experimental Results of Tool Wear and Spindle Loading

Experimental results					
Experiment No.	Spindle Speed (rpm)	Feed rate (mm/rev)	Depth of Cut (mm)	Tool wear (µm)	Spindle Loading (%)
1	900 (1)	0.14 (1)	0.50(1)	17	11
2	900 (1)	0.17 (2)	0.75 (2)	20	12
3	900 (1)	0.20 (3)	1.00 (3)	15	14
4	900 (1)	0.23 (4)	1.25 (4)	17	15
5	1000 (2)	0.14 (1)	0.75 (2)	11	11
6	1000 (2)	0.17 (2)	0.50 (1)	9	10
7	1000 (2)	0.20 (3)	1.25(4)	18	14
8	1000 (2)	0.23 (4)	1.00 (3)	16	13
9	1100 (3)	0.14 (1)	1.00 (3)	11	12
10	1100 (3)	0.17 (2)	1.25 (4)	22	13
11	1100 (3)	0.20 (3)	0.50 (1)	6	11
12	1100 (3)	0.23 (4)	0.75 (2)	15	13
13	1200 (4)	0.14 (1)	1.25 (4)	5	14
14	1200 (4)	0.17 (2)	1.00 (3)	13	13
15	1200 (4)	0.20 (3)	0.75 (2)	15	13
16	1200 (4)	0.23 (4)	0.50 (1)	7	12

A higher GRG means that the corresponding parameter combination is closer to the optimal. Values of grey relational grade with their corresponding orders are shown.

S/N ratios result is presented in Table 4.

Table 4. S/N Ratios Result

Experiment number	S/N Ratio (dB)	
	Tool wear	Spindle loading
1	-24.609	-20.828
2	-26.021	-21.584
3	-23.522	-22.923
4	-24.609	-23.522
5	-20.828	-20.828
6	-19.085	-20.000
7	-25.105	22.923
8	-24,082	22.279
9	-20.828	21.584
10	-26.848	-22.279
11	-15.563	-20.828
12	-23.522	-22.279
13	-13.979	-22.923
14	-22.279	-22.279
15	-23.522	-22.279
16	-16.902	-21.584
Maximum	-13.979	-20.000
Minimum	-26.848	-23.522

The distinguishing coefficient value is chosen to be 0.5. Values of grey relational generations, reference sequences and grey relational coefficients are shown in Table 5. Values of grey relational generations, reference sequences and the grey relational grade (GRG) are the average of the grey relational coefficient.

Table 5. Calculated Values of Grey Relational Grade

S. No.	GRGV		RSV		GRCV	
X ₀	1.000	1.000	1.000	1.000	1.000	1.000
1	0.826	0.235	0.174	0.765	0.742	0.395
2	0.936	0.450	0.064	0.550	0.886	0.476
3	0.742	0.830	0.258	0.170	0.659	0.746
4	0.826	1.000	0.174	0.000	0.742	1.000
5	0.532	0.235	0.468	0.765	0.517	0.395
6	0.397	0.000	0.603	1.000	0.453	0.333
7	0.865	0.830	0.135	0.170	0.787	0.746
8	0.785	0.647	0.215	0.353	0.699	0.586
9	0.532	0.450	0.468	0.550	0.517	0.476
10	1.000	0.647	0.000	0.353	1.000	0.586
11	0.123	0.235	0.877	0.765	0.363	0.395
12	0.742	0.647	0.258	0.353	0.659	0.586
13	0.000	0.830	1.000	0.170	0.333	0.746
14	0.645	0.647	0.355	0.353	0.585	0.586
15	0.742	0.647	0.258	0.353	0.659	0.586
16	0.227	0.450	0.773	0.550	0.393	0.476

Where, GRGV- Grey Relational Generation Value RSDC- Reference Sequence Definition Value GRCV- Grey Relational Coefficient Value

The grey relational grade represents the degree of correlation between the reference and comparability sequences. The higher value of the GRG corresponds to a relational degree between the reference sequence and the given sequence. The reference sequence represents the best process sequence. Therefore, a higher GRG means that the corresponding parameter combination is closer to the optimal.

Values of grey relational grade with their corresponding orders are shown in Table 6.

Analysis of variance (ANOVA) is carried out at significance level of $\alpha=0.05$ i.e. for a confidence level of 95%. ANOVA analysis for tool wear, spindle loading and grey relational grade are shown in Table 6, 7 and 8 respectively. Analysis of Variance for Tool Wear is shown in Table 6.

Table6. Analysis of Variance for Tool Wear

Source	DOF	SS	MS	F	P	C %
Spindle speed	3	105.187	35.062	1.548	0.296	27.98
Feed rate	3	50.187	16.729	0.739	0.566	13.35
Depth of cut	3	84.687	28.229	1.247	0.373	22.53
Error	6	135.875	22.646			36.14
Total	15	375.936				100

Table7. Analysis Of Variance for Spindle Loading

Source	DOF	SS	MS	F	P	C %
Spindle speed	3	3.187	1.062	17.000	0.002	11.41
Feed rate	3	5.189	1.729	27.667	0.001	18.57
Depth of cut	3	19.187	6.396	102.333	0.000	68.68
Error	6	0.375	0.062			1.34
Total	15	27.937				100

Table8. Analysis of Variance for means of Grey Relational Grade

Source	DOF	SS	MS	F	P	C %
Spindle speed	3	0.064	0.021	3.987	0.071	20.44
Feed rate	3	0.038	0.013	2.344	0.172	12.14
Depth of cut	3	0.179	0.060	11.087	0.007	57.18
Error	6	0.032	0.005			10.22
Total	15	0.313				100

Where, DOF- Degree of Freedom, SS- Sum of Squares, MS- Mean of Squares, F- A Statistical Parameter, P- Significance Value and C- Percentage Contribution.

4. Development of intelligent knowledge base system (IKBS)

One of the tools for closing the gap between design and manufacturing is application of artificial intelligent systems. The intelligent knowledge base system in concurrent engineering environment is used to optimize tool wear and spindle loading and manufacturing parameter for CNC lathe machine. The latest version of an artificial intelligent system shell (NEXPERT) based on object-oriented techniques (OOT) is used. A geometric description of the design feature of the component is sent for optimization and manufacturability evaluation at the various stages of product development. Within the manufacturing optimization, spindle load and tool wear are estimated. Feature based approach is used to obtain design specification. Design features are described in terms of its geometry and the amount of material to be subsequently removed. The properties of work piece materials, tool materials, and machining parameters are stored in data-bases. The intelligent system can retrieve information from the data bases or working memory and advise the designer or manufacturing engineers on the suitable choice of material, tool, and machining conditions. Figure 4 demonstrates intelligent system in computer base concurrent engineering environment. Flowchart of the intelligent system is shown in figure 5. A Hewlett Packard (HP) workstation is used in development of the intelligent systems. An intelligent knowledge based system is used in this approach to optimize design parameter including product cycle time and cost. An expert system for design and manufacturing for CNC machine center developed in a CE environment, the latest version of an expert system shell (NEXPERT), based on object-oriented techniques (OOT) is used. Figure 1 demonstrates how the system is worked in computer base concurrent engineering environment. A Hewlett Packard (HP) workstation was used in development of the expert systems. A geometric description of the design feature of the component is sent for optimization and manufacturability evaluation at the various stages of product development.

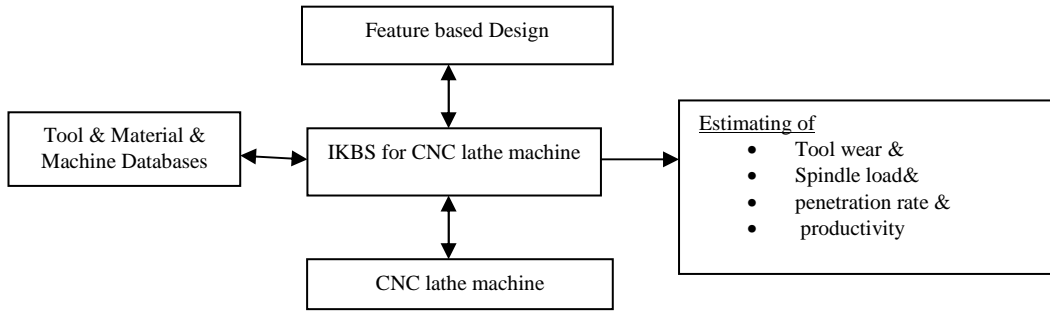


Figure 4. The Intelligent System in Concurrent Engineering Environment

Flowchart of the intelligent system is demonstrated in Figure 5. Within the optimization and manufacturability procedure, the machining cycle time, cost, feed, efficiency, and other machining are estimated. The need for efficient manufacturing has to be balanced against the cost and time needed to achieve a product of the right quality. Feature based approach is used to obtain design specification. Design features are described in terms of its geometry and the amount of material to be subsequently removed. The properties of work piece materials, tool materials, and machining parameters are stored in data-bases. The expert system can retrieve information from the data bases or working memory and advise the designer or manufacturing engineers on the suitable choice of material, tool, and machining conditions. The expert system also contains information needed for manufacturability evaluation and optimization, selection of alternative machining processes, knowledge of three dimensional design representations in terms of rules for good practice, machine and process capabilities, and constraints on features that can be manufactured by a particular process. For the present expert system knowledge has been gathered from experiments on machine center and experts. Machine cycle time and cost feed are also key factors, which depend on the type of material, tool and machining conditions. The choice of reasoning method, or a shell, is important, but it isn't as important as the accumulation of high-quality knowledge. Comparative experimental and artificial intelligent system results are demonstrated in Table 9.

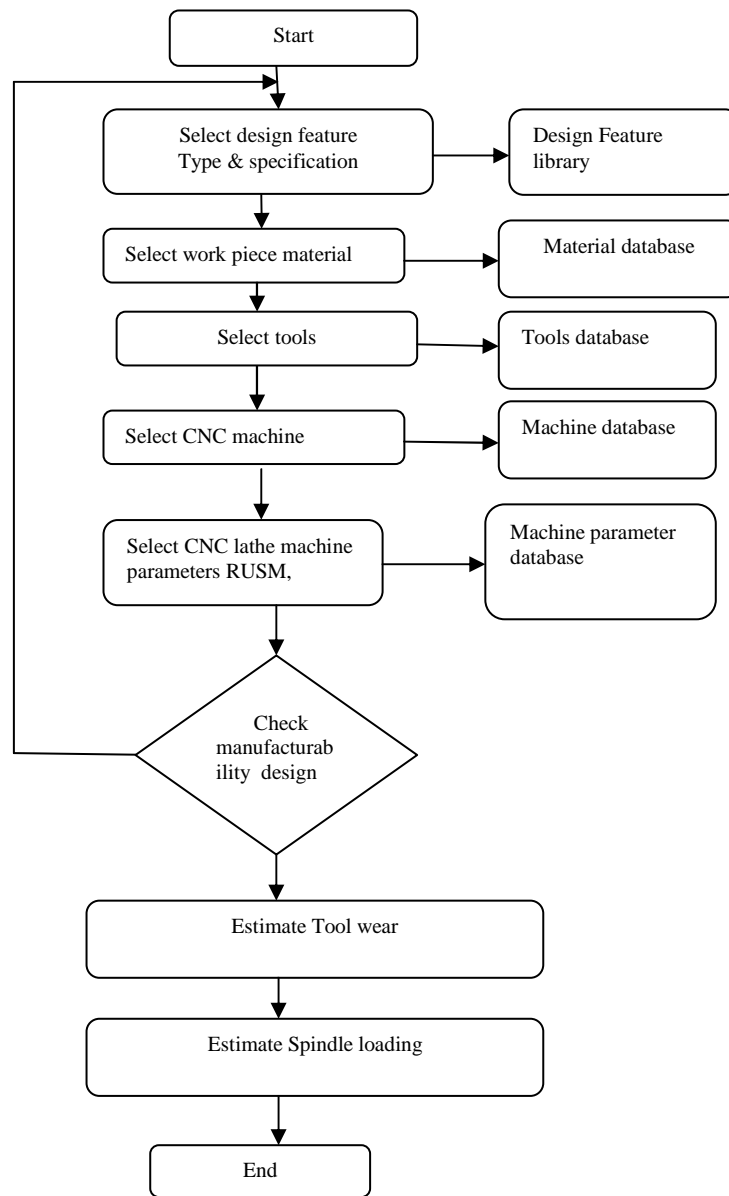


Figure 5. Flowchart of The Intelligent System

Comparative experimental results and artificial intelligent results are demonstrated in Table 9.

5. Conclusions

In this paper, an Intelligent knowledge based system (IKBS) was developed for optimizing dry CNC turning process using Taguchi method, CNC Machine, EN19 steel as the work piece material, and Cutting Insert were used. Tool wear and spindle loading which are the machining parameters, spindle speed, feed rate, and depth of cut, were optimized through the intelligent knowledge based system. The experimental CNC turning machine was used to evaluate IKBS. Intelligent system is developed to determine the effect of the machining parameters such as tool wear and spindle loading. The simultaneous optimization was done by intelligent system. Four levels of each

machining parameter were used in experimental verification on Model PTC 600, CNC lathe machinetool of PRAGA. The experimental verification designed based on Taguchi’s method was used to evaluate the effect of the machining parameters on individual responses of intelligent system. The simultaneous optimization is done by intelligent knowledge based system by changing parameters.

Table 9. Comparative Experimental Results and Artificial Intelligent System Results

Experimental results						Artificial intelligent system results				
Experimental results.No.	Spindle Speed (rpm)	Feedrate (mm/rev)	Depth of Cut (mm)	Tool wear (µm)	Spindle Loading (%)	Spindle Speed (rpm)	Feedrate (mm/rev)	Depth of Cut (mm)	Tool Wear (µm)	Spindle Loading (%)
1	900 (1)	0.14 (1)	0.50(1)	17	11	900 (1)	0.14(1)	0.50(1)	16	10
2	900 (1)	0.17 (2)	0.75 (2)	20	12	900 (1)	0.17(2)	0.75 (2)	19	11
3	900 (1)	0.20 (3)	1.00 (3)	15	14	900 (1)	0.20(3)	1.00 (3)	14	13
4	900 (1)	0.23 (4)	1.25 (4)	17	15	900 (1)	0.23(4)	1.25 (4)	16	14
5	1000 (2)	0.14 (1)	0.75 (2)	11	11	1000 (2)	0.14(1)	0.75 (2)	10	10
6	1000 (2)	0.17 (2)	0.50 (1)	9	10	1000 (2)	0.17(2)	0.50 (1)	8	9
7	1000 (2)	0.20 (3)	1.25(4)	18	14	1000(2)	0.20(3)	1.25(4)	17	13
8	1000 (2)	0.23 (4)	1.00 (3)	16	13	1000 (2)	0.23(4)	1.00 (3)	15	12
9	1100 (3)	0.14 (1)	1.00 (3)	11	12	1100 (3)	0.14(1)	1.00 (3)	10	11
10	1100 (3)	0.17 (2)	1.25 (4)	22	13	1100 (3)	0.17(2)	1.25 (4)	21	12
11	1100 (3)	0.20 (3)	0.50 (1)	6	11	1100 (3)	0.20(3)	0.50 (1)	5	10
12	1100 (3)	0.23 (4)	0.75 (2)	15	13	1100 (3)	0.23(4)	0.75 (2)	14	12
13	1200 (4)	0.14 (1)	1.25 (4)	5	14	1200 (4)	0.14(1)	1.25 (4)	4	13
14	1200 (4)	0.17 (2)	1.00 (3)	13	13	1200 (4)	0.17 2)	1.00 (3)	12	12
15	1200 (4)	0.20 (3)	0.75 (2)	15	13	1200 (4)	0.20 3)	0.75 (2)	14	12
16	1200 (4)	0.23 (4)	0.50 (1)	7	12	1200 (4)	0.23(4)	0.50 (1)	6	11

The optimization of complicated multi-performance characteristics was simplified through this approach. Tool wear and spindle loading are two characteristics on the basis of which the machining parameters, spindle speed, feed rate, loading and depth of cut were optimized through intelligent system. On the basis of the present work, the optimum value of multi-performance characteristics (lesser tool wear and low spindle loading) was obtained at spindle speed at 4 levels. The depth of cut has statistically significant effect while spindle speed has marginally significant effect on multi-performance characteristics. Table 3 demonstrated that in intelligent system on the basis of main effects plot, the optimum value of spindle loading is obtained at spindle speed of 1000 rpm, feed rate of 0.14 mm/rev and depth of cut of 0.5 mm. Also it is observed through main effects plot that the optimum value of tool wear is obtained at spindle speed of 1200 rpm, feed rate of 0.14 mm/rev and depth of cut of 0.5 mm. As observed through analysis of spindle loading, the percentage contribution of depth of cut is the largest i.e. 68.68%. The contribution of spindle speed and feed are 11.41% and 18.57% respectively.

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