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Process cost prediction: a soft computing approach

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Abstract

Purpose – Cost estimation based on expert's judgment is not an ideal approach, since human decisions are usually determined according to general attributes of limited and unstructured experience. The purpose of this paper is to develop a generic model of intelligence and cognitive science-based method that can play an active role in process cost prediction within the shortest possible time.

Design/methodology/approach – In this paper, an intelligent system was conceived for prediction of total process cost of the product. The system is based on the concept of case-based reasoning. It is a method for solving problems by making use of previous (source cases), similar situations and reusing information and knowledge about such situations. The source case data are generated by Taguchi technique and the cost function calculates the corresponding cost of each experiment in the economic time scale. The target case consists of the process variables whose cost needs to be determined. The cost for the source cases, consisting of the process variables of the already manufactured products are known in priori. The system calculates the similarities between the source cases and target cases and calculates the optimum cost. The fuzzy-C-means clustering method provides the model connecting the process parameters with total costs searched for.

Findings – The results show that the quality of predictions made by the intelligent system is comparable to the quality assured by the experienced expert. The proposed expert system is superior to traditional cost accounting system and assists inexperienced users in predicting the optimum process cost within the shortest possible time.

Research limitations/implications – The research was limited to the traditional machining process.

Practical implications – The paper can be applied to any process industry and will have immense practical value.

Originality/value – This is the first time an expert system has been developed for the process industry that can calculate the process cost within a few days or a few hours before making an offer to a buyer.

Keywords Taguchi methods, Fuzzy logic, Cluster analysis, Cost accounting, Intelligent agents

Paper type Research paper

1. Introduction

The capacity of the machine shop to respond quickly to the enquiry is an important factor of competitivity. On the basis of the enquiry, it must obtain the answer to the following questions within the shortest possible time:

- Are we in a position to make the product?
- Do we have the resources for the manufacture of the product?
- How much time do we need to be able to make the product?
- How much will be the cost of the product?

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The answers to the first two questions are rather trivial; if the company does not know the answers to these two questions it is likely for the company not to take the order at all. As the matter of fact the answers to these two questions are the results of cooperation between designers and technologists. The answer to the third question is very important particularly in the processing activities, since adhering to the delivery time is one of the most important factors of success. However, it is often difficult to answer that question, since the answer depends on a variety of interconnected factors. The answer to the fourth question, too, is very important. The preparation of a competitive offer and undertaking jobs is possible provided it is precise.

In this stage prior to undertaking an order manufacturing industry is busy with the problem of analyzing availability of resources and its characteristics influenced on processing the product. The product processing is a complex job including a variety of personnel, machines and technologies. Therefore, specifying the technological parameters like speed, feed, depth of cut (White, 1987), and their impact on the manufacturing costs poses a serious problem. In addition, this activity is very time limited. The output of this activity is of key importance for securing an order and for the business success of the order secured. The total increase in cost for the expected profit is an important piece of information that the company needs for negotiation with the buyer. The manufacturing cost can be rather analytically determined, but analysis requires additional time and cause additional costs. In answer to the enquiry, the offer must be prepared within the shortest possible time specified by the buyer.

It can be claimed that the problem of prediction of the total process cost has not been satisfactorily solved. Prediction relies too much on subjective influences of the experts. It is an evident that the described problem needs a better solution. A system is needed in the offerings stage to be able to determine the total production cost directly from the process variables and without the necessary expert knowledge. A fuzzy logic model is implemented in this system to deal with the uncertainty of process parameters and their relevant cost.

This paper comprises six sections. Section 2 presents the literature review. Section 3 describes various cost prediction methods. Section 4 presents the model of the intelligent system that incorporates Taguchi method for cost prediction. Section 5 deals with the use of the presented system on an example. In Section 6, the results are discussed and the guidelines for future researches indicated.

2. Prior art

The manufacturing companies always in search of automated process planning, a master database and optimum cost estimation technique (Nolen, 1989). The study (White, 1987) shows that process planning accounts for up to 58 percent of the total cost of manufacturing a part. Past studies reveal the knowledge-based system for process planning and cost estimation (Luong and Spedding, 1995). A major feature of this system is that it integrates the process sequence, machinability, and cost estimation. But, they do not select the optimum process parameters that have an impact on the production cost. One of the evaluation and optimization criteria for machining processes (Gayretli and Abdalla, 1999) is the manufacturing cost. The manufacturing cost estimation from the AND/OR tree representation (Wie and Egbelu, 2000) does not consider the robustness of the system rather it focuses on processing and material handling costs. The capability of selecting material, as well as machining process and parameters based on a set of design and production parameters and of estimating the product cost throughout the entire product development cycle including assembly cost (Shehab and Abdalla, 2002) has been depicted in the literature.

An intelligent life cycle cost (LCC) estimation system (Liu *et al.*, 2008) overcome the drawbacks of existing systems like low accuracy, and restriction to specific life cycle phases. The system allows the users to alternatively apply the activity-based costing technique and state-of-the-art machine learning techniques to define and estimate various LCC elements depending upon the information available in a product lifecycle database.

The feature-based cost-estimation method determines product's cost-related features and the associated cost for cost estimation. This approach is helpful essentially when the designer uses features at the design building block. A feature is the link between a simple geometric representation and the engineering application. The cost estimation of machined components is based on product features (Wie and Egbelu, 2000; Jong-Hun, 2002; Bouaziz *et al.*, 2006). In their work (Bouaziz *et al.*, 2006), semi-analytic approach has been used to group the complex machining features. Finally, for each feature parameter the system generates a process to be used as sample and consequently a model of machining time.

The methodology for modeling manufacturing costs at the design phase (Allen and Swift, 1990; Sheldon *et al.*, 1993; Hayes and Sun, 1995; Geiger and Dilts, 1996; Ou-Yang and Lin, 1997; Rehman and Guenov, 1998; Duran *et al.*, 2009) has been described in many articles. The instance updating process (Qing-Lan Han, 2009) can read the attribute value of design parameters from the design module instance library directly, optimize the modular cost and choose the right cost modular which meets the designed target, and rewrite the new instance into the modular cost instance library automatically.

The process-based cost modeling (Bloch and Ranganathan, 1992) takes into account the process yield at each step of the process sequence and how the yield at different steps impacts the overall cost of the module. The hybrid cost estimation system (Ben-Arieh, 2000) for rotational parts uses a combination of the variant approach and explicit cost calculation.

The expert system (Abdalla and Knight, 1994) for the concurrent product and process design of mechanical components provide high quality and lowest cost. Literature survey shows the mathematical model as well as algorithm (Feng *et al.*, 1996), use of software (Shing, 1999; McIlhenny *et al.*, 1993) for manufacturing cost estimation. Recent studies on cost estimation focus on artificial neural network (Cheng *et al.*, 2010) approach.

The prior art shows that a number of cost models have been developed for various kinds of application, but little effort was made in prediction of uncertainty of process cost within the shortest possible time.

To overcome this, an integrated framework PC-based system for prediction of process cost modeling to achieve several objectives is presented. The benefits of the proposed system are as follows:

- An expert system has been developed. The quality of prediction of the expert system is superior to traditional cost estimation system.
- The proposed system is useful before making an offer.
- The proposed system provides an opportunity to assist inexperienced users in predicting the optimum process cost.

- It advises users on how to eliminate design and production-related conflicts that may arise during the product development cycle.
- It improves the productivity of the machining component.

3. Cost prediction methods

The cost prediction methods (Wierda, 1990) have been divided into two parts. They are the global cost prediction method and detailed cost prediction method. The difference between these two methods is in terms of their speed, quantity of required information, costs, and areas of use. The global cost prediction methods are useful in early determination of costs and where no time and means are available for determination of costs. On the other hand, the detailed cost prediction methods are useful in the precise cost analysis of the finished product.

When predicting the costs in early stages of product development, we have to do with insufficient information about product and process. The methods differ particularly in volume of information they require. In early stages of design considerably less technological information is available than later on when the product has been finished. Therefore, in early stages of product design, in particularly the methods, requiring less information, are useful. These methods are mainly based on expert's intuition and establishing of similarities.

Therefore, different approximate methods of cost prediction have been developed:

- intuitive methods are based exclusively on the experts capabilities;
- in analog methods, costs are evaluated on the basis of similarity with other products;
- in parametric methods, costs are evaluated on the basis of the product characteristics which are in the form of parameters; and
- in analytical methods, costs are evaluated on the basis of the sum of the individual planned costs.

4. Model of intelligent system for prediction of process cost

It has been established that manufacturers most frequently use the intuitive prediction of total production costs. However, this approach is obsolete and the problem requires a better solution. Therefore, an intelligent system is needed to solve the existing problems.

In this research, we have conceived an intelligent system which is similar to the natural intelligent system, has the memory structured in the form of relation database. For preparing the prediction it uses the following steps:

(1) Collecting the process variables in the computer database.

(2) Perform experimental design using Taguchi technique and calculate cost of each experimental set-up.

(3) Collecting processes variables of new production process.

(4) Selecting the most similar cases (source cases) from the databases with the help of fuzzy-C-means (FCM).

Source cases are necessary for the use of case-based reasoning (CBR). Therefore, the information regarding the process variables must be collected in the company and conduct the matrix experiment. It is saved in the databases as logically connected technological information about the individual cases. The worked out model of the intelligent system for cost prediction contains:

- subsystem for collection of process variables;
- subsystem for determination of similarity;
- reasoning subsystem; and
- subsystem for use.

We must be aware that by today's artificial intelligence it is impossible to treat the entire product model as perceived by the human. However, even the experts do not have in memory the complete information about the product but only the most important parts and summaries. In this paper, similarity of the target case against other cases saved in the database is calculated. The similarity is calculated as the distance between the source cases and target cases. The greater the distance is the smaller the similarity between two products. In the further step, those most similar cases, which are then the input into the reasoning subsystem, are chosen.

For reasoning about the solution on the basis of similar cases the reasoning subsystem uses the artificial intelligence method of fuzzy inference system (FIS).

4.1 Case-based reasoning

The CBR technology is an artificial intelligence technique proposed in the early 1980s. It was first proposed by Schank and Abelson (1977). CBR is an analogical reasoning method. It provides both a methodology for building systems and a cognitive model of people. As a matter of fact, this is one of the most universal manners of problem solving, used frequently by the human in his work. It uses the recognizing way to modeling and explaining the human approach to solving problems in the areas where experience has a very important role.

CBR systems solve new problems by utilizing specific knowledge of past experience and basic competence is encoded within a corpus of previous problem solving episodes called case base (source). It can be presented in the form of numerical values. The target case is the description of the problem whose solution is searched for, whereas the source case is the description of the problem with known solution.

In our case, in the stage of adoption of solution the system uses Taguchi experimental design. The functional dependence of process variables calculates the production cost. Figure 1 shows the terminology and the principle of operation of the CBR applied to the problem being solved.

4.2 Identifying process parameters

The research carried out involved the development of robust process model for estimating cost of drilling operations. Particularly, within the aviation industry, the labor costs associated with the drilling process plays a significant role in the overall manufacturing cost. Hence, it is essential that effective methods can be used to develop process cost model. The traditional methods of estimating labor costs in the economic time scale exists between drilling time, feed rate, thickness, and hole diameter, i.e. as shown in equation (1):

$$T = \frac{3.14 \times D \times (t + C)}{Vf}, \tag{1}$$

T drilling time (s).

t thickness of material removed (mm).

D diameter of material removed (mm).

V surface speed of the drill (mm/s).

f feed (mm/rev).

C clearance distance (mm).

Hence, the process parameters of drilling operations are cutting speed, feed rate, thickness, and clearance. The Machinability Data Centre (1980) provides machining data. The machining data includes cutting speed, and feed rate. The aim of this research is to optimal selection of process parameters and prediction of the cost of the production process in the fuzzy environment.

4.3 Design for quality

Driven by the need to compete on cost and performance, many qualities conscious organizations are increasingly focusing on the optimization of process parameters. Taguchi emphasizes on the three steps for quality by design; system design, parameter design, and tolerance design (Taguchi, 1986; Phadke, 1989).

4.3.1 System design. System design is the process of applying scientific and engineering knowledge to produce a basic functional prototype design (Taguchi, 1986). The design includes the product design stage and the process design stage. This prototype model defines the configuration and attributes of the production process like selection of materials, components, and the selection of production equipment, and tentative process parameter values are involved. Since system design is an initial functional design, it may be far from reaching an optimum value in terms of quality and time value of money.

4.3.2 Parameter design. After the system architecture is decided on, the next step is parameter design. Parameter design is an investigation conducted to identify the setting of design parameters that optimizes the performance characteristics and reduce the sensitivity of engineering design to the sources of variation (Taguchi, 1986;

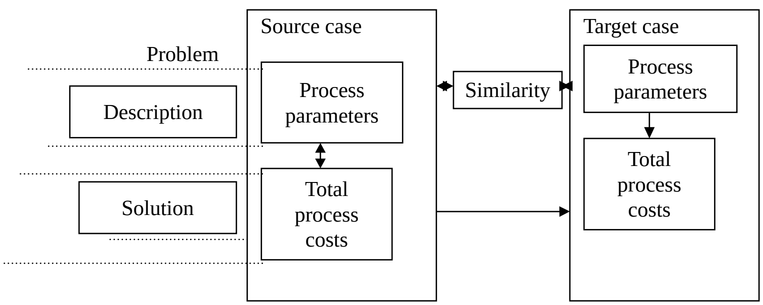

Figure 1. Principle of working of CBR

Bryne and Taguchi, 1986). Parameter design requires some form of experimentation for the evaluation of the effect of noise factors on the performance characteristics of the product defined by a given set of values for the designed parameters. Therefore, the parameter design is the key step in the Taguchi method to achieving high quality without increasing cost.

4.3.3 Taguchi method. Taguchi approach to parameter design provides the design with a systematic and efficient method for conducting experimentation to determine near optimum setting of design parameters (Taguchi, 1986). The Taguchi method uses orthogonal array (OA) from design of experiments theory to study the parameter space with a small number of experiments. This data are then used to predict the optimum combination of the design parameters.

4.3.4 Tolerance design. Tolerance design is the process of determining tolerances around the nominal settings identified in the parameter design process (Taguchi, 1986). Tolerance design is required if robust design cannot produce the required performance without costly special components or high-accuracy process. It involves tightening of tolerances on parameters where their variability could have a large negative effect on the final system.

4.4 Steps in Taguchi approach to parameter design

There are six steps in a typical parameter design study using the Taguchi approach (Taguchi, 1986). These are:

- *Step 1.* Identify the quality characteristic to be obtained and the objective function to be optimized.
- *Step 2.* Identify the design parameters and alternative levels.
- *Step 3.* Define possible interactions between theses parameters.
- *Step 4.* Design the matrix experiment and define the data analysis procedure.
- *Step 5.* Conduct the matrix experiment.
- *Step 6.* Analyze the data to determine optimum levels of design parameters and verify.

Steps 1-4 are used for planning the experiments. In Step 5, the experiment is conducted. In Step 6, the experimental results are analyzed to determine optimum levels, and a configuration experiment is conducted to verify the results.

5. An example: optimization of process parameters and prediction of process cost

The purpose of this study is to determine the best value of process control parameters and its corresponding cost. The best values of the parameters optimize the cost of the overall system. The parametric optimization has the following steps:

(1) *Identify the quality characteristics to be observed and the objective function to be optimized.* The quality characteristics to be observed are the minimum production cost. The objective is to determine the optimum combination of parameter values to obtain a minimum production cost.

(2) *Identify the design parameters and alternative levels*. For this study, the five parameters of interest that can significantly affect production cost were identified by the design engineers to be; thickness of the material, diameter, surface speed, feed, and clearance. The next step was to select feasible ranges over which each parameter would be varied in the analysis process. In parameter design, generally two or three levels or setting are selected for each parameter (Taguchi, 1986). The level of a parameter refers to how many test values of the parameters are to be analyzed over the feasible range. In this study, three levels of each parameter were studied, a high value (level 1), a medium value (level 2) and a low value (level 3). The levels and ranges of the five variables selected for study are given in Table I.

(3) *Define possible interactions between these parameters*. Varying several design parameters simultaneously may have interactive effects on the quality characteristics which can affect the optimum solution. In this study, main effect plot has been shown in Figure 2.

(4) *Design the matrix experiment and define the data analysis procedure*. The Taguchi method uses OAs based on the design of experiments theory to study a large number of decision variables with a small number of experiments. Using OAs significantly reduces the number or experimental configuration. In this paper, 27 experiments have been performed for analysis.

(5) *Conduct the matrix experiment*. The Taguchi approach to parameter design can be used in array situation where there is a controllable process. In most cases, computer models which model the response of many products and process can be used adequately to conduct the controlled matrix experiments. In this study,

Table I.
Factors and their levels

S. no.	Factors	Unit	Level 1	Level 2	Level 3
1	Thickness	mm	2.5	10	25.4
2	Diameter	mm	6.35	10	25.4
3	Speed	mm/s	180	350	550
4	Feed	mm/rev	0.15	0.45	1
5	Clearance	mm	1	2	3

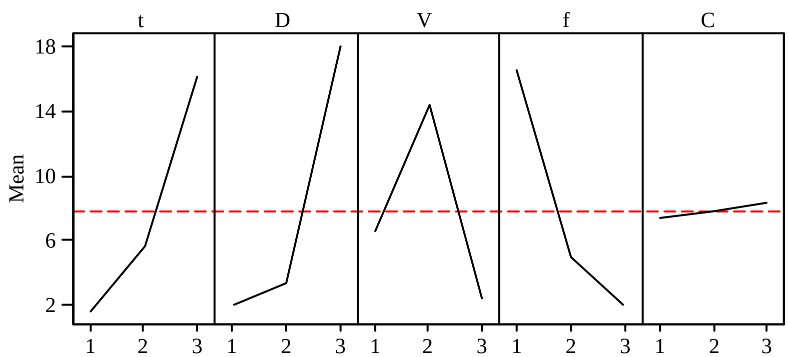

Figure 2.
Main effects plot for means

we select a row from the L_{27} OA and note the current value of each parameters of interest. Equation (2) is then used to generate the response of the overall system. The results of 27 experiments are presented in Table I. Table I shows that the cost of the system ranges from 0.507538 to 43.1442 in the time scale, depending on the levels of design parameters with an average cost of 7.839073 in the economic time scale.

(6) *Analyze the data to determine the optimum levels of design parameters to verify*. Since the experimental design is orthogonal, it is possible to separate out the effect of each parameter. The average cost for each parameters for the three levels are calculated and displayed in the response table given in Table I. The response table shows the cost effects of the parameters of each level. There are separate effects of each parameter and are commonly called main effects. The average costs shown in the response table are calculated by taking the average from Table II for a parameter at a given level, every time it was used. As an example the parameter thickness was at level three in experiments 19, 20, 21, 22, 23, 24, 25, 26, and 27. The average corresponding time is 16.20407 s. This procedure is repeated and the response table is completed for all parameters at each level. The cost effect sensitivity is computed by taking the difference between the largest and smallest cost for a given parameter. The response table

S. no.	Thickness (mm)	Diameter (mm)	Speed (mm/s)	Feed (mm/rev)	Clearance (mm)	Response
1	1	1	1	1	1	2.584685
2	1	1	1	1	2	3.323167
3	1	1	1	1	3	4.061648
4	1	2	2	2	1	0.697778
5	1	2	2	2	2	0.897143
6	1	2	2	2	3	1.096508
7	1	3	3	3	1	0.507538
8	1	3	3	3	2	0.652549
9	1	3	3	3	3	0.79756
10	2	1	2	3	1	0.626654
11	2	1	2	3	2	0.683623
12	2	1	2	3	3	0.740591
13	2	2	3	1	1	4.186667
14	2	2	3	1	2	4.567273
15	2	2	3	1	3	4.9477879
16	2	3	1	2	1	10.83106
17	2	3	1	2	2	11.8157
18	2	3	1	2	3	12.80035
19	3	1	3	2	1	2.126827
20	3	1	3	2	2	2.207388
21	3	1	3	2	3	2.28795
22	3	2	1	3	1	4.605333
23	3	2	1	3	2	4.779778
24	3	2	1	3	3	4.954222
25	3	3	2	1	1	40.10587
26	3	3	2	1	2	41.62504
27	3	3	2	1	3	43.1442

Table II. L_{27} matrix and experimental results

(Table III) shows that the diameter has the greatest sensitivity, meaning that the largest effect on cost is realized by varying this parameter. Similarly, clearance shows the least sensitivity.

5.1 Selecting control variables and experimental design

A primary goal in conducting a matrix experiment is to optimize the production process design, i.e to determine the best or the optimum level for each factor. According to the assessment system, the criteria and objects are, respectively, five and three. Therefore, the corresponding number of factors and levels are five and three to select L_{27} OA as the trial table (Tables I and II).

From the analysis, it is proved that by improving the quality Taguchi's method of parameter design at the lowest possible cost, it is possible to identify the optimum levels of factors at which noise factors effect on the response parameter is nominal. The outcome of this research is the optimized process parameter of the drilling operation which leads to minimum processing time in the economic scale. The optimized parameters levels are 16.2041, 18.0311, 14.4019, 16.5052, and 8.31454, respectively. Sensitivity analysis shows that diameter plays the most active role. The impact of clearance appears to be minimal. The main effects plot (Figure 2) displays the response means for each factor level in sorted order. A horizontal line is drawn at the grand mean. The effects are the difference between the means and the reference line.

5.2 FCM clustering and analysis of the result

Clustering is a very effective technique to identify natural groupings of data from a large dataset, thereby allowing concise representation of a system behavior. A fuzzy technique is implemented in this system to deal with uncertain knowledge on cost estimation. Fuzzy logic model follows several steps. These steps are fuzzy sets of input variables and output variables. Each variable has number of memberships. The main process in the fuzzy model is fuzzification of inputs, fuzzy inference based on defined set of rules, and, finally defuzzification of the inferred fuzzy values. In order to explain the steps in developing fuzzy model, an example of a fuzzy logic system capable of estimating the machining time in economic scale is presented. The input variables are thickness of material, diameter of the material, surface speed of the drill, feed, and clearance. Membership functions and range of each variable has been shown in Table I. In this paper, FCM technique allows to group various process parameters of machining component. These parameters are specified by a membership grade. FCM provides a method that shows grouping the data points (Figure 3) in a multi-dimensional space into a specific numbers of different clusters. Clustering data (Figure 4) shows the relationship between the input variables and output variables. The cluster centers (C) has 12 rows represents 12 clusters with six columns representing the position of the

Level	t (mm)	D (mm)	V (mm/s)	F (mm)	C (mm)
1	1.6243	2.0714	6.6395	16.5052	7.36360
2	5.6889	3.4147	14.4019	4.9734	7.83907
3	16.2041	18.0311	2.4757	2.0386	8.31454
Sensitivity	14.5798	15.9597	11.9262	14.4665	0.95094
Rank	2	1	4	3	5

Table III. Response table for mean

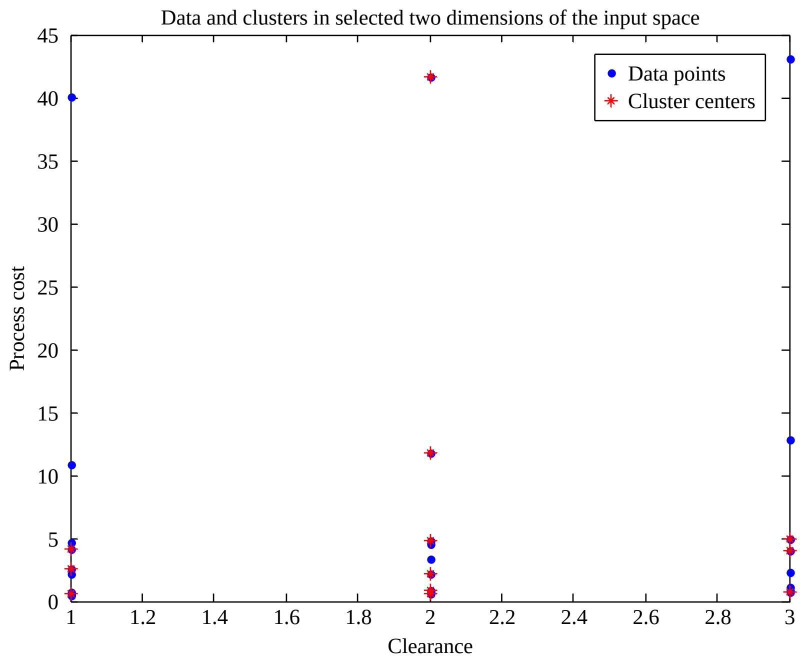

Figure 3.
Cluster centers in the "clearance" and "process cost" dimensions of the input space

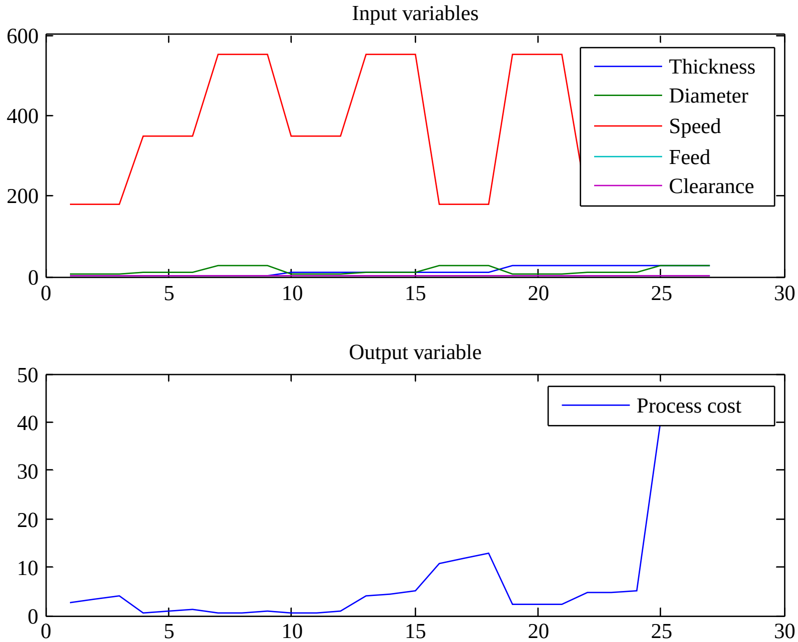

Figure 4.
Input and output variables

clusters in each dimension has been shown in Table IV. In this paper, radii of '1' has been considered as cluster center. The variable (S) specifies the range of influence of cluster center in each of the data dimensions. Table V shows the variable (S) has six columns representing the influence of the cluster centers on each of the six dimensions. As shown in Figures 5 and 6, there are five input variables and one output variable. Since the member of rules equals the number of clusters and hence 12 rules (Figure 7) are created. Figure 5 shows the total number of fuzzy rules used in the example.

Table IV.
Cluster centers

2.5000	10.0000	350.0000	0.4500	2.0000	0.8971
25.4000	6.3500	550.0000	0.4500	2.0000	2.2074
25.4000	10.0000	180.0000	1.0000	2.0000	4.7798
25.4000	25.4000	350.0000	0.1500	2.0000	41.6250
2.5000	25.4000	550.0000	1.0000	2.0000	0.6525
10.0000	25.4000	180.0000	0.4500	2.0000	11.8157
2.5000	6.3500	180.0000	0.1500	3.0000	4.0616
10.0000	10.0000	550.0000	0.1500	1.0000	4.1867
10.0000	6.3500	350.0000	1.0000	1.0000	0.6267
2.5000	6.3500	180.0000	0.1500	1.0000	2.5847
10.0000	10.0000	550.0000	0.1500	3.0000	4.9479
10.0000	6.3500	350.0000	1.0000	3.0000	0.7406

Table V.
Sigma values

8.0964	6.7352	130.8148	0.3005	0.7071	15.0743

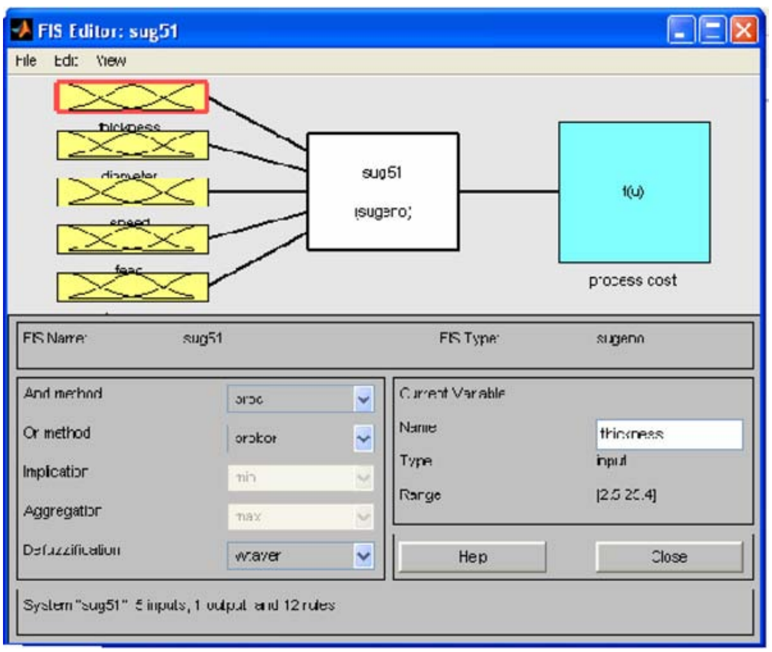

Figure 5.
The graphical editor for building FISs

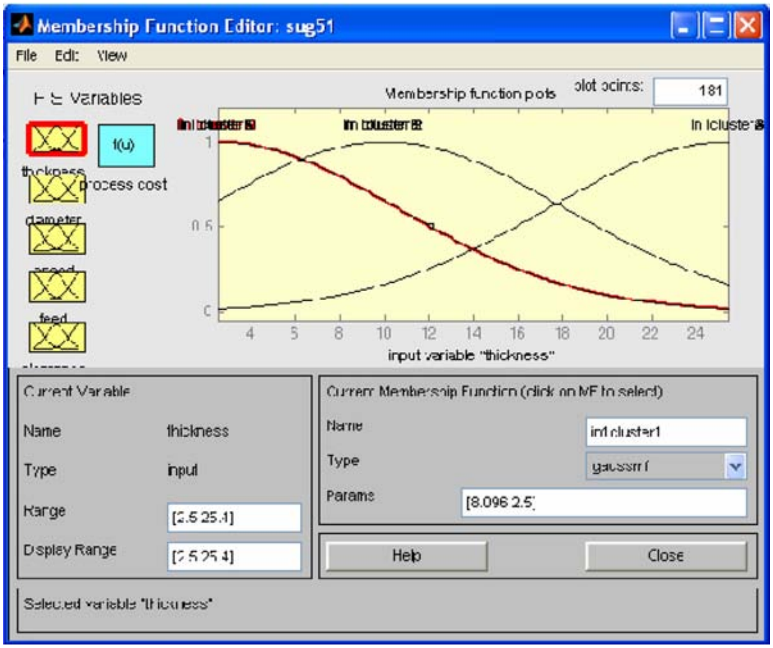

Figure 6.
The graphical membership function editor

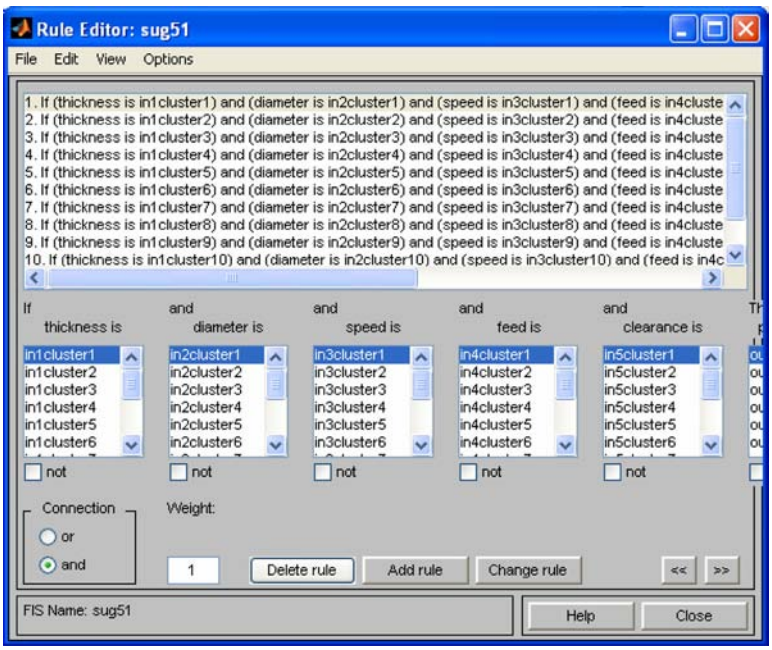

Figure 7.
The graphical rule editor

Matlab software simulates the response of the fuzzy system for the entire range of inputs that the system is configured to work for. Thereafter, the output or the response of the FIS to the inputs is plotted against the inputs as a surface. It indicates behavior of the system for the entire range of values in the input space. In the plot (Figure 8), the surface viewer shows the process cost increases with increase in thickness and diameter. Finally, rule viewer (Figure 9) simulates the FIS response for specific values of the input process parameters.

6. Discussion and conclusion

Cost estimation in the fuzzy environment may be useful when the cost estimator does not have data that allows the construction of cost-estimating relationships in the traditional manner. In this paper, CBR-based method used to predict the process cost in the fuzzy environment. A fuzzy technique is implemented in this system to deal with uncertainty in cost estimating knowledge. It has been used as the basis for controlling the production process. This is because it does not require the use of complex mathematical models. The difference between a fuzzy expert system and the traditional expert system is that the reasoning process used is different. In the case of an expert system, production rules are used to define cost-estimating knowledge. Production rules capture knowledge in the form of "if [...] then [...]" statements. A fuzzy production rule is similar to the conventional type of production rule except that the conditions in the production rules are replaced with linguistic expressions to which truth values are assigned.

In this paper, we have conceived a general concept of the intelligent system that integrates fuzzy logic and Taguchi experimental design for predicting the total process cost. We have decided on building intelligent system due to awareness that the problems

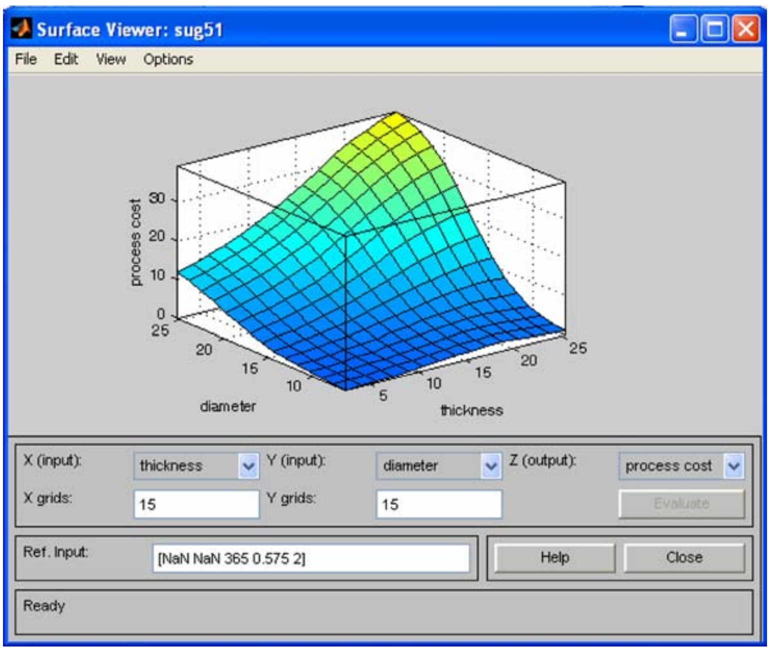

Figure 8.
Input-output surface viewer

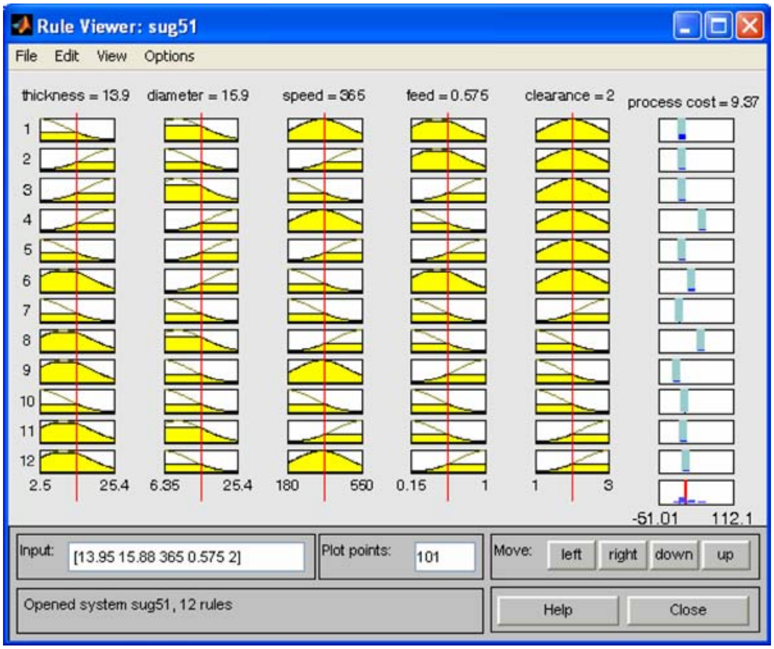

Figure 9.
Rule viewer that simulates the entire fuzzy inference process

treated cannot be solved by experts' judgments. The system built on the basis of our model is viewed as usually particularly in preparation of offers for the machined component on the basis of process parameter analysis.

Testing of the system has brought interesting insights and many future challenges. It would be too much to expect that the system will make very precise predictions, since even experienced experts cannot do that. However, we must be aware that enough properly similar cases are needed for the prediction of adequate quality. In this study, qualitative factors have been ignored. The qualitative and quantitative factors of machining process should be considered in the future work. In addition to that this paper may be extended by increasing the number of parameters and applying this method in the different manufacturing processes.

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